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Democracy Under Uncertainty:

The “Wisdom of Crowds” and the Free-Rider Problem in Group Decision Making

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Abstract

We introduce a game theory model of individual decisions to cooperate by contributing personal resources to group decisions versus by free-riding on the contributions of other members. In contrast to most public-goods games that assume group returns are linear in individual contributions, the present model assumes decreasing marginal group production as a function of aggregate individual contributions. This diminishing marginal returns assumption is more realistic and generates starkly different predictions compared to the linear model. One important implication is that, under most conditions, there exist equilibria where some, but not all members of a group contribute, even with completely self-interested motives. An agent-based simulation confirms the individual and group advantages of the equilibria in which behavioral asymmetry emerges from a game structure that is *a priori* perfectly symmetric for all agents (all agents have the same payoff function and action space, but take different actions in equilibria). And a behavioral experiment demonstrates that cooperators and free-riders coexist in a stable manner in groups performing with the non-linear production function. A collateral result demonstrates that, compared to a “dictatorial” decision scheme guided by the best member in a group, the majority-plurality decision rules can pool information effectively and produce greater individual net welfare at equilibrium, even if free-riding is not sanctioned. This is an original proof that cooperation in ad hoc decision-making groups can be understood in terms of self-interested motivations and that, despite the free-rider problem, majority-plurality decision rules can function robustly as simple, efficient social

decision heuristics.

Key words: group decision making under uncertainty, free-rider problem, majority-plurality rules, marginally-diminishing group returns, evolutionary games, behavioral experiment

Democracy Under Uncertainty:

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Every human society relies on groups to make important decisions because, among other advantages, groups have more problem-solving resources than any individual member (e.g., Kerr & Tindale, 2004). Indeed, there are many tasks that can be achieved only by a group effort and that could never be accomplished by one individual or by many individuals working separately. For example, a group of geologists, engineers, demographers, and business executives have complementary skill sets that could allow them to make much more precise decisions about where to locate a large construction project than any one of the individuals in these groups could alone. Similarly, in a primitive setting, five tribesmen could cooperate to decide where to forage for prey much more effectively than if all worked independently.

But, despite such a potential for “collective wisdom,” there is a fundamental trade-off between selfish, individualistic goals and the more general social welfare. Participation in a group activity is often described as a sacrifice of personal utility. Who hasn’t pondered whether to “blow-off” preparation for a group assignment (e.g., not to study the candidates’ resumes before a hiring committee meeting, to shirk one’s homework before a joint study committee meeting, etc.) and to “free-ride” on the efforts of those who have fulfilled their social obligation? Many theoretical analyses of small group cooperation conceptualize group enterprises as social dilemmas, and treat cooperative behavior as a puzzle (Dawes, 1980). In social dilemma situations, the

personal payoff to an individual group member is always less when s/he cooperates in the group enterprise than it would be if s/he acted as a free rider, even though the overall group welfare is larger when all members cooperate than when nobody cooperates. Consistent with the “sacrifice theme,” most behavioral experiments on social dilemmas show that average contributions to public goods deteriorate significantly after a few iterations if no punishment opportunity exists (e.g., Fehr & Gächter, 2002; Herrmann, Thöni & Gächter, 2008; for reviews, see Camerer, 2003; Fehr & Fischbacher, 2003; Ledyard, 1995). Even with an alternative public goods game featuring a preliminary binding commitment round, which produces more theoretical and empirical support for at least some players to make social contributions, the prevailing interpretation holds that cooperation is difficult to sustain (Saijo and Yamato, 1999; Cason, Saijo and Yamato, 2002; Cason, Saijo, Yamato and Yokotani, 2004). And, in conventional group production and problem-solving tasks, social psychological research has provided considerable evidence of social loafing (Latané, Williams & Harkins, 1979; see also Kerr & Tindale, 2004; Williams, Harkins & Karau, 2003 for reviews). If members of small decision-making groups (e.g., juries, panels, committees) are playing such a game, the theory predicts that cooperation is hard to sustain without enforcement mechanisms. This framing of group enterprises as social dilemmas leads to a pessimistic view of groups as problem solvers or decision makers and implies that public goods requiring group cooperation will be severely under-supplied.

The above sketch illustrates a fundamental gap between the two images of group

decision mechanisms – a highly intelligent device that can achieve collective wisdom versus a defective social process that degrades towards sub-optimal performance (Janis, 1972). How can we reconcile the two contrasting images? The central puzzle is as follows: How can the “wisdom of crowds” (Surowiecki, 2004) be sustained in face of the free-rider problem? Do groups require some policing mechanism that enforces members’ contributions toward group enterprises to yield collective wisdom?

Is Group Decision Making Necessarily a Social Dilemma?

To defend the viability of group decision processes, some social choice theorists have argued that people may feel good, experiencing “expressive benefits” (Brennan & Lomasky, 1993), when they contribute to the functioning of a group (Downs, 1957) or when they fulfill civic duties (Meehl, 1997; Riker & Ordeshook, 1973). Survey data from large-scale elections provide modest support for this view, while identifying other social-psychological factors as well, including social norms (Knack, 1992) and cognitive biases (Opp, 2001). Applying this view to small-group decision making, we would expect some people to be cooperative – for example, turning out for group meetings, engaging in costly information search prior to meetings – driven by these prosocial motives.

Although prosocial motives underlie some contributions to group enterprises, such an account begs questions concerning the ultimate sources of these motives (see Posner, 2000). The present paper proposes an alternative theoretical framework in which to interpret positive contributions to group enterprises without invoking prosocial

motives. After all, there must be some personal advantage to individual members in cases where no collection of individuals acting independently could achieve even part of the group product that can be achieved by the collective. But even in tasks where contributions are incremental, we argue that contrary to the social dilemma interpretation, cooperation can in many real-world and theoretical contexts (i.e., with diminishing marginal group returns to individual contributions) be both self-interested and beneficial to the group. Such an analysis would explain the widespread cooperation in human societies as a function of the benefits of *individual* cooperation without adding any new prosocial motives. Our argument draws on a diverse sample of empirical and theoretical literatures, ranging from theoretical biology to experimental economics. We first analyze structures of various group tasks in natural settings, in terms of functional relations between members' inputs and group productivity (McGrath, 1984; Steiner, 1972). We then discuss the implications of this analysis for cooperation in group decision making.

The ubiquity of marginally-diminishing-returns group production function in naturally-occurring tasks. When a group of people collaborates to make a decision or to produce some other tangible good (e.g., investment committee, strategic planning staff, production line), productivity usually increases monotonically with increases in group size, at least over some range. But the relationship often falls short of linearity. Although we cannot conduct a census of all group production tasks in our society, we are confident that the almost universal relationship between group size and productivity is

monotonically increasing but with marginally-diminishing returns over an appropriately specified range in group size. This can be observed in many natural settings.

The behavioral ecology literature studying animal behavior provides a useful starting point to see why this is the case. Marginally-diminishing returns are common in many systems of the animal kingdom, including social vertebrates and social insects (Foster, 2004). For example, sentinel behavior of many mammals and birds is a collective endeavor with marginally-diminishing returns (Trivers, 1971; Bednekoff, 1997). Think of it this way: if you are camping with a group of 10 people, there are much larger benefits from the first and perhaps second person staying awake to warn the other campers about approaching bears than there are from the 9th and 10th campers staying awake, whose contributions generate virtually zero marginal benefits.

To illustrate, let us denote the average probability of a single sentinel detecting an approaching predator as p . Assuming that there is no process loss (Steiner, 1972), the probability that a group with n individuals being on watch detects the danger successfully is then approximated by $1-(1-p)^n$ (Laughlin, 1980; Lorge & Solomon, 1955). This means that the group success in vigilance increases monotonically but diminishes at the margin, with an increase in the number of sentinels, n , in the group. Social foraging, another key survival task, shares this structure. When a flock of birds is searching for food, discovery of a rich food patch by a single bird results in other birds joining to forage in the same patch (Giraldeau & Caraco, 2000). The group success in locating a rich food patch is thus approximated by the identical function, $1-(1-p)^n$, where p denotes

the average probability of a single bird encountering a rich patch and n refers to the flock size (Barnard & Sibly, 1981; see Foster, 2004, for other examples in the animal kingdom).

Although many core everyday group-production tasks for humans also revolve around foraging and risk-monitoring (see Kameda & Tindale 2006 for review), “groups” in these animal examples are surely nothing more than collections of individuals, where no substantial coordination activities exist. Birds do not deliberately orchestrate their sentinel or food-searching behavior, and group performance is best described as a probabilistic aggregation of individual outputs rather than the product of a systematic group design (e.g., group decision making), which is more typical of human social coordination.

Interestingly, however, explicit coordination efforts do not necessarily eliminate the marginally-diminishing nature of group production for the following reasons. First, difficulties in coordination among members multiply with group size, and interpersonal conflicts are also likelier to occur, among other production-cutting social factors (see Steiner, 1972; Thompson, 2004, especially Chapter 2, for comprehensive reviews). Second and more importantly, the fundamental structure of many natural tasks mandates diminishing returns in productivity from later contributions. When information is redundant or task-relevant skills overlap from member to member, diminishing returns are inevitable even with perfect coordination (Clemen & Winkler, 1999; Makradakis & Winkler, 1983); and when any task is *not* perfectly divisible into independent sub-tasks,

individual performances must be somewhat redundant, producing diminishing productivity as more individuals are added to the collective enterprise.

For example, consider group judgments that rely on information aggregation, which represents an essential sub-task in group performance (McGrath, 1984). Members collectively estimate a quantity, such as the future price of a stock. Let us presume that the group estimate is approximated by the arithmetic mean, or simple average, of the individual estimates, which is a valid description of many behavioral judgment aggregation processes (see Clemen & Winkler, 1999; Hastie, 1986; Kerr, MacCoun, & Kramer, 1996, for review). Furthermore, if individual estimates have equal signal-to-noise ratios and vary around the true value of the stock price with uncorrelated random errors, the arithmetic mean is a statistically optimal aggregation rule (Larrick & Soll, 2006; Surowiecki, 2004). For an average computed from a randomly drawn sample, the law of large numbers tells us the group estimate should converge on the true value, and well-known calculations of the variance of the arithmetic mean show explicitly that the precision of this group estimate improves with each additional observation (i.e., an individual's judgment in the present example). The reduction in expected squared error by adding one more member to an n -person group, $\frac{\sigma^2}{n(n+1)} (= \frac{\sigma^2}{n+1} - \frac{\sigma^2}{n})$, is greater than zero, where σ^2 is the variance of the individual estimates. But note the marginal improvements in the aggregate estimate (in terms of smaller random deviations from the true value) diminish with increasing group size, n (see Condorcet, 1785/1994, for an analogous proof when the judgment is categorical, e.g.,

between political candidates).

Indeed, if we turn to classic analyses of group performance and productivity in social psychology (McGrath, 1982; Steiner, 1972), we find that many abstract task types imply that group performance indices (amount of goods produced, time to produce, accuracy of estimates) will be related to group size with a monotonically increasing but marginally diminishing returns function. This includes decisions based on unanimous, majority, and truth-wins group decision rules (see Condorcet 1785/1994; Smoke & Zajonc, 1962); disjunctive tasks (Steiner, 1972) where a success of only one member is sufficient to achieve a collective goal (e.g., risk-monitoring, resource-finding, and other “Eureka problems”: see Kameda & Tamura, 2007; Laughlin, 1980; Lorge & Solomon, 1955; Taylor & Faust, 1952); and additive tasks (Steiner, 1972) where members’ inputs are summed to determine an overall group performance (e.g., group estimation by averaging, physical tasks as exemplified by a tug of war: see Hastie, 1986; Ingham, Levinger, Graves & Peckham, 1974; Kravitz & Martin 1986). The only clear exceptions to this generalization are conjunctive tasks (Steiner, 1972) where the “weakest link” member determines the overall group performance and more members mean poorer performance, and synergistic tasks where the group production function would be positively accelerated. We know of no examples of the deliberate use of groups to solve conjunctive tasks (unless institutional or situational constraints impose conjunctive task demands) and we know of very few examples of verified synergistic group performances in the scientific literature (see Larson 2009 for a recent comprehensive review).

In summary, a marginally-diminishing group production function seems to apply in many group performance domains in natural settings. Perhaps because of the mathematical convenience of the linear group production function, this widespread diminishing marginal returns feature is conspicuously missing from most of the group performance and public goods literatures (see also Kerr 1983 for one of early attempts to link group performance with social dilemmas). The linear public goods model assumes that each individual's contribution yields a constant return for the group, and the return, which is shared evenly by all members, is less than individual cost of cooperation, regardless of the number of other contributors. This implies the overly pessimistic prediction that we should almost never expect to see contributors to public goods because, at all levels of inputs in the group production function, defection is the dominant strategy (Ledyard, 1995; but see Laury & Holt, 2008).¹

Emergence of a mixed equilibrium. Given a marginally-diminishing production function, is defection still the dominant strategy? The answer turns out to be *not necessarily*. A theoretical biologist, Motro (1991), concerned with abstract foraging problems, has provided a general powerful framework in which to analyze this question. Let us suppose that we have a six-person group and that the group production function (e.g., mapping the number of contributors who search for food into the expected quantity of food available for each member of the group, humans, non-human animals, robots, etc.) takes a marginally diminishing form as shown in Figure 1. As in social dilemmas, we assume the group production benefit is shared equally by all group members, but that

production costs are borne by each producing or contributing member individually (Dawes, 1980; Kameda, Takezawa, & Hastie, 2003). The x-axis represents the number of cooperators, while the y-axis represents the expected gross return to each member of the group (group gross return / 6). “Gross” refers to the fact that the *costs* of contributing are not yet represented in Figure 1. The production function’s concave increasing form generates marginal returns to individual contributions to the group, labeled δ_n when the number of cooperators increases from n to $n+1$, that are indeed diminishing as more individuals contribute.

Motro (1991) analytically identified an Evolutionarily Stable Strategy (ESS) in this situation: Cooperate as long as the increment, δ , exceeds individual cost (denoted c), but switch to defection otherwise.² In other words, keep cooperating while your contribution yields an individually positive expected *net* return. Note that, even when the increment δ representing the marginal individual return to contributing is too small to justify the cost to contribute for an individual, additional contribution by the individual may still be beneficial to the entire group (i.e., while the marginal individual return, δ_m , by joining m other cooperators in the group is less than individual cost, c , aggregate group return, $6*\delta_m$, may still be greater than the individual cost). This means that, as in linear social dilemmas (Dawes, 1980), each individual’s rational action may lead to the inefficient level of contributions at the group level (“Pareto inefficient”). However, in the nonlinear case depicted in Figure 1, δ is not constant but is a function of the number of cooperators. As long as $c < \delta_n$ for some small n , the model predicts that some

members in the group will contribute/cooperate; in other words, the important implication of diminishing returns in this empirically more realistic group production function is that defection is no longer a universally (i.e., over the entire range of number of cooperators) dominant strategy. Thus, many naturally-occurring tasks with marginally-diminishing return curves do not necessarily constitute social dilemmas.

INSERT FIGURE 1 – ILLUSTRATION OF A MARGINALLY-DIMINISHING
RETURN CURVE

Figure 2 re-expresses the production function from Figure 1 as a *net* (individual gross return – cost) payoff function for a cooperator (solid curve), and as a *net* payoff function for a defector (dashed curve), both expressed as functions of the number of other group members who contribute (individual cooperation cost was fixed at 0.7 in Figure 2). Note that the two curves intersect at an equilibrium, specifying the number that is predicted by the theory of Nash Equilibrium of rationally self-interested cooperators in the group. As can be seen in the figure, an individual is personally better off cooperating when there are few cooperators, and better off defecting when there are already several cooperators among the other group members. The net benefits of cooperating or defecting depends on the frequency of the alternative strategy within the group; neither strategy is dominant (Laury & Holt, 2008). Too many players opting for one strategy reduces its relative profitability while increasing the profitability of its

alternative, providing an incentive for individuals to switch. Since the two strategies are mutually constrained in terms of relative profitability, we expect a mixed equilibrium to emerge (Gintis, 2000; Maynard Smith, 1982). At equilibrium, the group reaches a stable state in which complementary proportions of cooperators and defectors coexist, achieving an average frequency of cooperators given by the point at which the two individual net payoff curves intersect. In Figure 2, the two curves intersect when the number of other cooperators is between 1 and 2, which predicts 2 cooperators and 4 defectors on average in the group with the illustrative costs and benefits of cooperation in this example.

INSERT FIGURE 2 – EXPECTED INDIVIDUAL NET PAYOFFS (INDIVIDUAL GROSS
RETURN – COST)

Group Decision Making Under Uncertainty

Motro's (1991) model provides a powerful theoretical benchmark to re-consider realistic cooperation levels in group performance and public goods provision (Kerr, 1983; Laury & Holt, 2008). We apply this model to a stylized group decision situation, which constitutes a core group-production task in everyday life. We have two goals in this paper: (1) to examine the degree to which Motro's framework captures members' cooperation for the group enterprise, and (2) to examine the effects of various voting

rules (e.g., Majority/Plurality, Best Member Rule) on the quality of group decision outcomes when free-riding is possible.

Applicability of Motro's model to group decision making. Suppose that a group of six members needs to select a single location in which they will search together for food. Each member decides whether to “cooperate” (produce) by seeking decision-relevant information, an activity with some personal costs; or to free-ride (defect, scrounge) on the decisions of the other members. Obviously, if no member decides to seek information, the group decision will be uninformed and far from optimal. But, it is also true that, if all members seek information, there will be redundancy and a loss of potential production value. Motro (1991) proved that it is wasteful for all individuals to seek information precisely because of the diminishing marginal returns of the group production function. We apply this logic to group decision making under uncertainty, where the objective value of a choice alternative, or “truth” (Laughlin, 1980), must be inferred through imperfect stochastic information. We predict that group decision making under uncertainty, which forms the core of modern committee meetings as well as “primordial” team foraging, would yield a mixed equilibrium in which cooperators and free-riders coexist, rather than the all-defect equilibrium in social dilemmas (with the unrealistic linear-additive production function; see also footnote 1). An equilibrium mixture of cooperators and defectors will be determined by the Motro function.

Robustness of majority/plurality group decision rule. Although the argument so far has depicted group decision making as if it were a uniform concept,

each group decision setting entails specific design features. Even if we limit our focus to “consensual” decision making (e.g., juries, committees, panels), there are numerous variations about how to implement the group decision system. This includes choices of quorum rules, polling procedures, aggregation rules, and so on (e.g., Hastie, Penrod & Pennington, 1983; Kameda, Tindale, & Davis, 2003; Regenwetter, Grofman, Marley & Tsetlin, 2006). How do these design features affect members’ cooperation levels and consequentially determine the quality of final group decision outcomes? In this paper, we test whether the Majority/Plurality rule, whereby the option in the group’s choice set with the most votes becomes the group’s final choice, can sustain members’ cooperation and serve as a robust truth-seeking decision procedure in uncertain environments (Hastie & Kameda, 2005; Sorkin, Hays & West, 2001).

Using computer simulations and a behavioral experiment, Hastie and Kameda (2005) evaluated various group decision rules based on their adaptive accuracy in choosing the mutually most beneficial alternative in an uncertain, simulated test bed environment. These aggregation rules included Averaging, the Best Member Rule, Condorcet Majority, Majority/Plurality, and so on (see Hastie & Kameda, 2005 for details). When the adaptive success standard is applied to evaluate the rules (Hammond & Stewart, 2001; Hastie, 1986; Gigerenzer, Todd, and the ABC Research Group, 1999), the Majority/Plurality rule fares quite well, performing at levels comparable to much more cognitively-taxing rules such as the averaging rule. The Majority/Plurality rule also matches the computationally demanding Condorcet Majority Winner that is the common standard in evaluations of preferential choice rules (Arrow,

1951; Mueller, 2003; Regenwetter, Ho & Tsetlin, 2007). These results indicate that, despite its computational simplicity, the Majority/Plurality rule can achieve surprisingly high levels of performance under uncertainty.

In these previous studies, however, it was assumed that everybody would cooperate to support the group enterprise (Hastie & Kameda, 2005; Sorkin et al., 2001). Thus, it is an open question, whether the Majority/Plurality rule would be theoretically and behaviorally successful when there is a personal cost to be an informed voter. Several key questions in the present research concern the performance of the Majority/Plurality rule under more realistic assumptions about the group production function and individual cooperation costs. If a mixed equilibrium holds (Motro, 1991), how efficient is the productivity at the equilibrium under the Majority/Plurality group decision rule? Does the Majority/Plurality rule degrade into a universal free-riding “tragedy of the commons” situation where decisions are made by uninformed voters (Downs, 1957; Mueller, 2003)? How does it compare with the group outcome guided by the best and brightest “benevolent dictator” in a group – a logically coherent decision system that has been pitted against democratic rules in the social choice literature (Arrow, 1951; Laughlin, 2006) and a solution that is selected in some naturally-occurring human groups?

In the following, we first report on an evolutionary computer simulation (Kameda et al., 2003; Smith & Conrey, 2007; Kenrick, Li & Butner, 2003) to determine if there is a mixed equilibrium in a “group-foraging” task with significant and stable levels of cooperation under different group decision rules, and then compare adaptive success of

the different decision rules at respective equilibria. Next, we report a behavioral experiment that implements a group foraging task under uncertainty in an interactive laboratory set-up. In both cases, individuals (computer agents in the simulation study and human participants in the behavioral experiment) were required to decide whether to cooperate or defect before voting on a foraging location.

EVOLUTIONARY COMPUTER SIMULATION

Overview

We rely on an evolutionary simulation model based on Darwinian logic to explore the implications of the diminishing group returns model and to evaluate the theoretical viability of a Majority/Plurality group decision rule when informed participation in the decision is individually costly. In the evolutionary simulation, we first specify a set of behavioral strategies, and then let them interact in the same population (e.g., Axelrod, 1984; Gintis, 2000; Kameda et al., 2003). The strategies are defined in terms of the basic cooperate (at personal cost) versus defect (at no personal cost) distinction. The Darwinian logic dictates that more successful strategies in the current population reproduce at higher rates for the next generation, analogous to biological evolution in an ecological niche. In social scientific applications, such changes are not necessarily evolutionary but may reflect, most notably, social imitative learning of successful strategies in a group (Gintis, 2000). We observe whether such a change in the population structure leads to a stable collective state where the population is dominated by a set of strategies (or a strategy) and no further changes occur. If it does, the stable

end state is called an evolutionary equilibrium (Gintis, 2000; Maynard Smith, 1982).

In the following simulations, we formulate four behavioral strategies in terms of the basic distinction between cooperating (at a personal cost) versus defecting (at no personal cost): (a) whether to pay a cost to acquire the information needed to make well-informed individual judgments, and (b) whether to pay a cost in order to vote. Individual cooperation (information search and voting) can increase the quality of group decisions and thus enhance overall group return, but it entails a personal cost as well, which presents a dilemma for the agent in deciding at what level to take part in collective action.

Given such a dilemma, it seems that uncooperative members are unilaterally better off than cooperative members, and we might expect them eventually to dominate the population, which would yield an all-defect equilibrium. But based on Motro's model (1991), we posit that a mixed equilibrium will emerge, where both cooperative and uncooperative individuals coexist in the population. We test this prediction in two populations governed by contrasting decision rules: the Majority/Plurality Rule (based on the winner with the most votes in a one-member-one-vote election) versus the Best-Member Rule (where the member with the best long-term ability/accuracy dictates the choice). As a benchmark, we also examine a population operating with the Random-Member Rule (where a randomly-chosen member dictates the choice to the other members) as in Hastie & Kameda (2005).

If a mixed equilibrium indeed emerges for each population as predicted by the

model, we will consider our second question: Does the Majority/Plurality Rule produce better outcomes in terms of individual net benefit than the Best-Member Rule at the respective equilibrium in each population? Is the “wisdom of crowds” sustained over time or does the Majority/Plurality Rule unravel into a free-riding world in which decisions are made predominantly by uninformed voters?

Simulation Method

Simulation platform

To illustrate the basic features of our simulation, we rely on the metaphor of a primitive forager seeking resources at locations in an uncertain physical environment (see Hastie & Kameda, 2005, for more details on the procedure). This task represents the essential features of a general decision problem faced by any organism: Which option among a set of alternatives to choose, given noisy information about the payoff contingent on choosing each option. The simulation world has two major components, environmental events, namely the amounts of reward (gain or loss) available at various locations, and foragers whose fitness depends on accurate judgments of the environmental events (see Figure 3). The state of an environmental event (reward available) is known probabilistically to foragers through proximal, partially valid cues (i.e., a noisy cue is the true value plus a white-noise error term). Thus, each individual faces the adaptive task of aggregating the information contained in these noisy cues to infer whether environmental locations are rewarding or punishing. The individual reward judgment process is a direct implementation of Brunswik’s general “Lens Model”

framework for perception and judgment (Brunswik, 1955; Cooksey, 1998; Hammond & Stewart, 2001; Gigerenzer et al., 1999).

 INSERT FIGURE 3 - STRUCTURE OF THE ENVIRONMENT

Structure of the environment. In the simulation, we set up the stochastic features of environmental events as follows. Let j index one of 10 possible foraging locations, $j \in \{1, 2, \dots, 10\}$. To represent the true value of the food available at each of these 10 locations, we generated random numbers from a normal distribution $N(0, 30)$ denoted, Q_j (we refer to this quantity as the “payoff” in this paper). Motivation for the units used (e.g., standard deviation equal to 30) is discussed below. These true values, however, cannot be directly known; information about each of the 10 values represented by Q_j is available in three noisy cues. These cues were generated by taking each location’s true resource value, Q_j , and adding normally distributed error to it, creating a cue value composed of true value + error. The normally distributed error terms were specified with standard deviations of 10, 20, and 30. Therefore, the cues, denoted (C_1 , C_2 , C_3), differed in validity as predictors of the true value of each patch, with validities of 0.90, 0.69, and 0.50, respectively, on a proportion-of-variance-accounted-for metric (i.e., R-squared). As shown in the left portion of Figure 3, the optimal linear combination of these cues for estimation (explaining 92% of the variance of Q_j) was:

$$E[Q_j | C_1, C_2, C_3] = 0.68C_1 + 0.17C_2 + 0.08C_3. \quad (1)$$

Foragers. As evident from the discussion above, the adaptive goal for each individual “forager” is to combine the cues, in the same manner as the optimal linear combination rule, to yield an estimate for value of the payoff (i.e., “expected nutritional value”) available at each location. Such an individual estimation process, which we refer to as a judgment policy (Brunswik, 1955; Hammond & Stewart, 2001), can be represented by how the person weights the three proximal cues to form an estimate. Our simulation implemented this feature by assigning judgment policies to foragers at random as follows (see the right portion of Figure 3).

Member i 's estimation of location j 's value is expressed (i = member, j = location, and k = cue):

$$\text{estimated } Q_{ij} = w_{i.1}C_{ij1} + w_{i.2}C_{ij2} + w_{i.3}C_{ij3} \quad (2)$$

where $w_{i.1}$ is the weight forager i gives to his or her perception of Cue 1 for location j , denoted C_{ij1} . The model allows agents to experience perceptual errors. In other words, cue values are not usually perceived veridically and different judges make different errors. Each perceived cue value, C_{ijk} , has two components: a true cue value ($C_{.jk}$) that is common to all members, plus an environmental-perceptual error (e_{ijk}), associated uniquely with each member i 's perception of the cue ($C_{ijk} = C_{.jk} + e_{ijk}$). The error component, e_{ijk} , is generated randomly from $N(0, 20)$.

We relied on Dawes' (1979; also Brehmer & Joyce, 1988, and Anderson, 1981) observation that, in judgment tasks such as the one in our simulations, people appear to use simplified linear aggregation rules. Instead of using optimal weights (e.g., Equation

1), people judge as though they rely on approximate weights and often on equal weights, getting the predictive “direction” right, but only approximating relative cue importance. (Dawes [1979] also demonstrated that such “improper linear models” achieve levels of accuracy comparable to optimal linear aggregation rules in many situations; see also Gigerenzer, et al., 1999, for analyses of other simplified estimation rules).

Dawes’ (1979) conclusion implies that most people would weight the three cues approximately equally in aggregation. Based on this reasoning, our simulation used the following procedure in the implementation of $w_{i,k}$. For each member of each foraging group, we generated three random numbers once and then standardized them so that their sum equaled 1. The standardized fractions determined the member’s judgment policy which remained identical throughout the group’s 100 “hunts”. Thus, the modal judgment policy under this procedure is equal cue weighting, (.33, .33, .33), but there is considerable variation in individual cue weighting policies. The important point is that a modal forager’s estimates in the basic simulation are not statistically optimal (see Eq. 1), but on average are based on equal cue weights.

Behavioral strategies of the foragers

Members’ judgment policies for cue-weighting were the only individual differences that Hastie and Kameda (2005) considered in their simulation platform; these are cognitive differences among members. To address the issue of the free-rider problem in group decision-making, the current simulation introduced members’ motivational differences for cooperation as a key element in the evolutionary algorithm. Initially, we focused on two dimensions that often underlie members’ cooperation in

group decision-making (Downs, 1957; Riker & Ordeshook, 1973): (a) whether to accept the information search cost to make well-informed individual judgments (Lupia, 2002; Kameda & Nakanishi, 2002, 2003), and (b) whether to bear the cost of participating (voting) in group meetings (Knack, 1992). As shown in Table 1, each dimension had two behavioral options, creating four “genotypes”.

INSERT TABLE 1 – FOUR BEHAVIORAL STRATEGIES

For the search dimension, some agents engage in individual information search about the environment and personally incur some cost (a simulation parameter to be varied systematically) to obtain that information. These “searchers” have access to the environmental cues in all ten locations (Figure 3) and combine them according to their judgment policies. Other agents (“non-searchers”) skip information search to avoid the search cost. Accordingly, they have no cue information to inform their judgments, and if non-searchers “vote” (see below), they endorse one alternative randomly (essentially introducing “noise” into the group decision). As in many public goods situations, group payoffs are equally available to all irrespective of members’ cooperation levels.

We quickly discovered, however, that only two of the four original strategies could survive at the equilibrium: searcher/voter hybrids and non-searcher/abstainer hybrids. The other two hybrids, searcher/abstainer and non-searcher/voter, disappeared in the course of Darwinian selection. These two hybrids are “evolutionarily irrational”

behavioral choices in this model in that they cannot sustain themselves (searchers who abstain from voting harm themselves by wasting resources expended on information search, while non-searchers who vote also harm themselves by degrading the accuracy of group decisions in terms of average payoff). Thus, we collapsed the 2 x 2 system of genotypes into a dichotomous cooperator (producer) versus defector (scrounger) classification, which we use from now on in reporting the results of the simulation study. (In the behavioral experiment to be reported subsequently, it remains an empirical question what frequencies of these four behavioral genotypes will be observed.)

These strategies were subject to evolutionary selection in the simulation in that the prevalence of each genotype in the population was adjusted over time based on the behavioral payoffs that they received in the past; more successful strategies reproduced at a higher rate in later generations.³

Evolutionary algorithm

The evolutionary algorithm is summarized in Figure 4. For illustration, let us consider a population governed by the Majority/Plurality Rule. For each simulation run, we started with an equal probability (0.50) that any member would be assigned to one of the two behavioral strategies. Next, 12-person teams were formed by randomly selecting individuals of various genotypes. Using the metaphor of foraging, this twelve-person team goes on a “hunt” together.

INSERT FIGURE 4 – EVOLUTIONARY ALGORITHM

For each hunt, members behave according to their assigned strategies. The group members are first provided an opportunity to acquire information about the current environment. Searcher/voters engage in individual learning of the three cues for each of ten locations at some personal cost which was assumed to be constant across foragers (cost was varied as a simulation parameter). They rely on these three cues to choose the best alternative based on their judgment policies (Figure 3; see also footnote 3). Non-searcher/abstainers skip the individual learning, avoid the cost, and do not vote or otherwise influence the group decision.

Searcher/voters' opinions are then aggregated by the Majority/Plurality Rule; selecting the location endorsed by the greatest number of voters in the meeting. In case of a tie, one of the alternatives (of those endorsed by at least one voter) is selected at random. Payoff accruing from the group's collective choice (i.e., the payoff available in the chosen patch) is equally shared among all members, whereas the corresponding costs are subtracted from the shares for the cooperative searcher/voters.

The group repeats the same process for 100 different hunts in a new environment on each hunt. The entire routine runs for 10,000 12-member groups, based upon which we calculated the mean net benefit (fitness) for each of the two strategies, by collapsing their net behavioral outcomes (individual gross return – cost) over 1,000,000 (100 x 10,000) trials.

One “generation” ends here and, according to the Darwinian logic, agents with

more fit strategies produce slightly more offspring for the next generation. We formulated the selection mechanism by a standard numerical technique called the replicator dynamic (see Gintis, 2000). In the replicator dynamic, a strategy associated with a fitness greater than the average fitness in the current generation increases in frequency in the next generation, while a strategy associated with a fitness less than the average decreases (see Appendix A for details). Using this idealized evolutionary process, we observed adjustments in the population strategy structure over generations.

The simulation repeated the above steps for many generations until an equilibrium state emerged in the population. The equilibrium refers to a state where no further changes occur in the distribution of strategies in the population. In the simulation, we terminated iterations when changes in proportions of the strategies between two consecutive generations dropped below .0001.

As noted, we created three types of populations (“societies”), one governed by the Majority/Plurality Rule; one governed by a Best-Member Rule, where the most competent member (i.e., the member whose judgment policy was closest to the optimal weighting) among the searcher/voters in each group was initially designated the leader and made the decisions for the subsequent 100 hunts, and the other governed by a Random-Member Rule, where one searcher/voter in each group was initially selected at random and made decisions for the 100 hunts. For each of the three decision rule societies respectively, we conducted separate simulation runs to see if an equilibrium state emerged. When the equilibrium was reached in each society, we compared the

three societies (governed by different decision-making rules) in terms of average individual net benefits (“individual fitness”).

Simulation Results and Discussion

Emergence of a mixed equilibrium over time

We systematically varied the cost parameters for cooperation (cost parameters for information search and voting) and the number-of-resource-locations parameter. We fixed the group size at 12 throughout the simulation runs. Figure 5 displays equilibrium proportions of the two viable strategies (searcher/voters versus non-searcher/abstainers) in each population (Majority/Plurality Rule, Best-Member Rule, or Random-Member Rule), as a function of the total cooperation cost (the figure shows simulation results when the number of resource locations was set at 10; later we will show results from a sensitivity analysis where the two parameters were varied simultaneously).

 INSERT FIGURE 5 – EQUILIBRIUM PROPORTIONS OF THE STRATEGIES

As expected, a mixed equilibrium emerged in each of the three societies. For example, when the cooperation cost was set at 0.03, 45% were cooperative searcher/voter hybrids in the Majority/Plurality Rule population, 39% in the Best-Member Rule population, and 35% in the Random-Member Rule population.⁴ Rather than being dominated solely by the free-riding non-searcher/abstainer hybrids, the cooperative

searcher/voter hybrids sustained themselves in a stable manner. These results support our hypothesis that cooperation in group decision-making under uncertainty can be conceptualized as a game where a mixed equilibrium exists (Motro, 1991; Laury & Holt, 2008).

Individual net benefits

Given the emergence of the mixed equilibrium, we can address our next question: Does the Majority/Plurality Rule produce better results for individuals in terms of average net benefits than the Best-Member Rule, when incentives for free-riding exist? Figure 6 displays individual net benefits (individual gross return – cost) at the respective equilibriums in the three societies, as a function of total cooperation cost.

 INSERT FIGURE 6 – INDIVIDUAL NET PAYOFF AT THE EQUILIBRIUM

Individuals in the Majority/Plurality Rule population were better off than those in the Best-Member Rule population, who were substantially better off than the Random-Member Rule population, for the parameter range displayed in Figure 6. However, notice also that the difference in net benefits between the two key populations decreased as the cooperation costs increased. This suggests that the superiority of the Majority/Plurality Rule over the Best-Member Rule may be eliminated and even reversed when cooperation costs are high. Indeed, this was the case in all the simulations we ran.

When the cooperation cost was 0.27 or higher (see footnote 4), the relative standings of the two rules were reversed [these points are not displayed in Figure 6 to simplify the graphic representation].

How can we interpret these patterns? A close inspection of the equilibrium proportions of cooperative and defecting individuals in the population (see Figure 5) provides some insights. Figure 5 shows that the proportions of searcher/voter hybrids decreased monotonically with a higher cooperation-cost. For example, in the Majority/Plurality Rule population, the proportion of the cooperative individuals dropped to 27% when the cost was 0.15 (on the right side of the diagram). This implies that, with the increase in cooperation cost, the average frequency of searcher/voter hybrids (cooperators) in each 12-person group could eventually fall below three ($\approx 12 \times 0.27$). Notice that three is the minimum number of voters for the Majority/Plurality Rule to be meaningfully compared with the Best-Member Rule and other group decision processes, as if the frequency of voters is less than three, no majority/plurality can be defined among the voters, except for the theoretically trivial case of perfect agreement. In other words, when the cooperation cost is high, searcher/voter hybrids become so rare that most decision-making groups fail to assemble the critical voter-quorum (three). In these circumstances, the Best-Member Rule beats the “indecisive” Majority/Plurality Rule.

Sensitivity analysis

In order to see how robust these findings were, we conducted a sensitivity analysis varying key parameters: the number of choice alternatives (from two to 11) and

the cooperation costs (from 0.03 to 0.27), with group size held constant at 12. A mixed equilibrium, as we observed in Figure 5, emerged for all combinations of these parameter values. Given this, we only report relative standings of the Majority/Plurality Rule to the Best-Member Rule in terms of individual net payoffs at the respective equilibria. Figure 7 displays differences in individual net benefits between the two populations (Majority/Plurality Rule minus Best-Member Rule) as a joint function of the cooperation costs and the number of alternatives. In the iceberg-shaped surface, the unshaded (“above water”) regions refer to parametric combinations where the Majority/Plurality Rule outperformed the Best-Member Rule (i.e., the net benefits difference score was greater than zero), and the shaded (“underwater”) regions refer to the reverse situation.

INSERT FIGURE 7 – SENSITIVITY ANALYSIS

First, as we saw in Figure 6, the relative advantage of the Majority/Plurality Rule over the Best-Member Rule decreased monotonically, and was eventually reversed with higher cooperation costs (represented on the x-axis). As the cooperation costs increased, the equilibrium proportion of searcher/voter hybrids in the population decreased and groups operating with the Majority/Plurality Rule could rarely assemble 3 voters. Second, the Majority/Plurality Rule was more successful with greater numbers of choice alternatives (the second abscissa). As can be seen in the figure, the unshaded regions in the graph, where the Majority/Plurality Rule outperformed the Best-Member Rule, were

larger with more locations (in general, more elements in the group's choice set).

To summarize, the sensitivity analysis demonstrated that the Majority/Plurality Rule was more successful than the Best-Member Rule when the cooperation cost was small and when there were more locations (i.e., choice-alternatives in the group's choice set). (Of course, if cooperation costs are extremely high, no one will cooperate and all decision rules will perform at equally low levels.) These results suggest that, despite the inherent free-rider problems in group decision making, there exist large parametric regions where the Majority/Plurality Rule is successful in an uncertain game against nature.

BEHAVIORAL EXPERIMENT

The next step is to see how these theoretical results fare as hypotheses about the behavior of human decision-making groups. For this purpose, we designed a laboratory task where we could compare the performance of the Majority/Plurality Rule and the Best-Member Rule, while measuring each member's cooperation during the decision-making process. Based on the simulation results, we predict: (a) that participants will be divided into one of the two behavioral types, searcher/voter hybrids (cooperators) or non-searcher/abstainer (defectors) hybrids, and (b) that the proportions of these two types of members will stabilize over time, consistent with the expectation of a mixed equilibrium. We also predict (c) that groups governed by Majority/Plurality Rule will be better off than those governed by the Best-Member Rule in terms of individual net payoffs. Of course, the simulation model suggests that this prediction is

parameter-dependent (Figure 7); our aim is to provide an empirical demonstration (or an “existence proof”) of one case where majoritarian decision rule works well under uncertainty in face of the free-rider problem.

Method

Participants

Participants were 180 undergraduate students (127 males and 53 females) enrolled in introductory psychology classes at Hokkaido University.

Group Decision Task

We implemented a hunting-under-uncertainty task through a Local Area Network in a behavioral laboratory. We told participants that they were members of six-person teams that must choose one of ten locations in which to hunt (instead of 12-person groups assumed in the simulation, we used 6-person groups in the experiment due to practical constraints). Resource levels (e.g., prey values) in each location were generated randomly from a normal distribution $N(80, 30)$ [unit = 1 yen]. The resource levels could only be estimated on the basis of three stochastic cues that differed in predictive validity and “perceptual errors,” analogous to the model in the previous section. The parametric set-ups for the cue structure and the perception errors were identical to those used in the simulation reported here in Figure 3.⁵

The group decision task was to select the most profitable location, using either the Majority/Plurality Rule or the Best-Member Rule. These rules were assigned to each

group at the outset. Participants' rewards were made contingent upon their performance in the hunts. Specifically, resources in the chosen patch were divided evenly among all six members, although cooperative members (who engaged in information search and/or voting) incurred personal costs, which were subtracted from their individual accounts.

Procedure

Six participants were randomly assigned to one of two decision-rule conditions (Majority/Plurality or Best-Member), in experimental sessions lasting approximately one hour. There were 15 groups (90 participants) in each condition. Upon arrival, each participant was seated in a private cubicle and received instructions individually via computer displays. After the hunting-under-uncertainty task was explained, participants were provided an opportunity to familiarize themselves about how to use the three stochastic cues (see Figure 3 for the cue structure), displayed on the screen for each of the ten locations. For 20 practice trials, each participant made personal judgments as to the most profitable location out of ten alternatives. On each of the 20 practice trials, they received feedback about their choice success, in terms of the discrepancy in resource levels between the chosen location and the most profitable one (the most profitable location was also identified on the screen). Because this was a practice session, all the judgments in this phase were individual, without reward.

Majority/Plurality Rule versus Best-Member Rule. After practicing the cue-based judgment under uncertainty task, participants were told they were members of a six-person hunting-team seeking the most profitable location out of ten. They were

told that their rewards in the experiment would be contingent on the success of their group decisions. Participants in the Majority/Plurality Rule condition were told that the location endorsed by the greatest number of voters would be designated as their collective choice by the computer. Participants in the Best-Member Rule condition were told that the best individual (who was most accurate in the practice session) among the voters on each “hunt” would be automatically selected by the computer (anonymously), and that participant’s choice would be designated the group choice.

Costs for cooperation. Costs (incentives for free-riding) were introduced as follows: First, members who chose to collect environmental information, when forming individual judgments, had to pay 3 yen. Second, voters who chose to participate in a group meeting to express their preferences had to pay another 3 yen. However, the payoff from the selected location was to be equally shared among all six members whether they incurred costs or not. The experiment consisted of 24 trials with 3 new hunts in each trial. Before each of the 24 trials, each participant was asked whether he or she wanted to pay 3 yen for information search and whether to pay 3 yen to vote on the trial (these decisions were made independently).⁶ Only individuals who had paid the information search cost could access the environmental cues when forming individual judgments, while those who had not paid the search cost could not access the cue information in the three hunts during that trial. And, only individuals who had paid the voting cost were able to express their preferences during that trial. For each hunt, the group decision was reached by aggregating these voters’ preferences via either the

Majority/Plurality Rule or the Best-Member Rule (the aggregation was conducted by the computer).

Outcome feedback. After each of the 24 trials, participants were provided private feedback. The feedback consisted of their personal net benefit earned during the trial (i.e., evenly split share of the sum of group outcomes from the three hunts minus an individual's own cooperation costs) and the number of group members who voted during the trial.⁷ Through the summary feedback, participants could learn how well they performed on the trial and adjust their cooperation levels on the next trial. Unlike the practice session, no specific feedback was provided as to personal accuracy.

Results and Discussion

Emergence of stable cooperation over time

Our evolutionary simulation model suggested that group decision making under uncertainty would eventually yield a mixed equilibrium, where cooperative and uncooperative individuals coexist in a stable manner. Specifically, we predicted that participants would be divided into one of the two behavioral types over time, searcher/voter hybrids versus non-searcher/abstainer hybrids, and that proportions of these two types of members would stabilize.⁸

Interlocked information-search strategies and the voting strategies. We examined how frequently each participant showed the behavioral linkage between the choices of information search strategy and voting that we observed in the simulation. For this analysis, we divided the 24 trials into three 8-trial-blocks. Figure 8 shows mean

proportions of the trials in each block, where participants' strategic choices were coherent, i.e., either totally cooperative (searcher/voter hybrid) or totally uncooperative (non-searcher/abstainer hybrid).

INSERT FIGURE 8 – INTERLOCKING BETWEEN THE TWO STRATEGIES

Consistent with the simulation, mean proportions of the coherent choices (searcher/voter hybrids and non-searcher/abstainer hybrids) increased over time, reaching nearly 100% coherence in the last block. A 2 (condition) x 3 (block) x 15 (group) Analysis of Variance (using a hierarchical linear model) yielded a main effect for block, $F(2, 52) = 36.52, p < .001$. This means that, if an individual voted in the last block of the experiment, she or he, with probability very close to 1, had also engaged in costly individual information search. Voting by ignorant members in truth-seeking situations (e.g., “group foraging”) would be self-defeating in terms of individual net payoff, because it would degrade the overall quality of group decisions, while exacting a personal voting cost (Lupia, 1994). If members are aware of these cost issues, a behavioral linkage between information search strategy and voting should emerge voluntarily without social enforcement mechanisms in truth-seeking groups, as in the present experiment.

Stabilization of cooperation (searcher/voter hybrids) over time. Were the cooperative members (search/voter hybrids) able to sustain themselves in actual groups,

as predicted by the evolutionary simulation model? Or, was the coherent-choice pattern due to the tendency of uncooperative members (non-searcher/abstainer hybrids) eventually to dominate groups? For this analysis, we estimated the theoretical equilibrium frequency of cooperators in each condition. We first estimated the empirical group and individual payoff functions by means of an econometric procedure, and then estimated the equilibrium frequency and the Pareto-optimum frequency for the Majority/Plurality Rule (see Appendix B for the estimation procedure).

Figure 9 displays mean frequencies of the cooperative members in each group across the 24 trials, along with the equilibrium frequency and the Pareto optimum (local and global) frequency in the Majority/Plurality Rule condition.⁹ Although the mean frequencies of cooperative searcher/voter hybrids slightly decreased over trials, about half of members remained cooperative on the last trial. Notice that the mean frequency of cooperative members in the Majority/Plurality Rule condition was 3.13 on the final trial and was significantly greater than the equilibrium frequency ($t(14) = 3.89$, $p < .001$). Indeed, the modal number of cooperators across all groups in all trials in the Majority/Plurality Rule condition was 3, with more than 75% of observed action profiles containing 3 or more cooperators. Figure 10 displays the empirical distribution of the numbers of group members who cooperated (N) across 360 observations (15 groups x 24 trials).

INSERT FIGURE 9 – MEAN FREQUENCIES OF COOPERATIVE MEMBERS

INSERT FIGURE 10 – FREQUENCY DISTRIBUTION OF NUMBER OF
COOPERATORS IN GROUPS IN THE MAJORITY/PLURALITY RULE CONDITION

Notice also that variances associated with the mean frequencies, as depicted by vertical bars in Figure 9, decreased over time in both conditions. Dividing the 24 trials into three 8-trial-blocks, a 2 (condition) x 3 (block) repeated measures ANOVA on the variability index revealed a significant main effect for block, $F(2,56) = 8.02$, $p < .001$. Thus, most groups stably functioned at a locally Pareto efficient level of public goods contributions, with 3 contributors and 3 free-riders per group. The unambiguous modal value (Figure 10) is remarkable in finding a locally best outcome in group terms despite the fact that the individual incentives built into the game structure would predict far less cooperation at $N=1$ (see Appendix B).

Did the stabilization in cooperation rates occur at the aggregate level or at the individual level? That is, did *different* individuals cooperate on each trial or did the *same* individuals cooperate (and the others consistently defect) across trials? Figure 11 displays how frequently individual participants cooperated during each of the three blocks in the Majority/Plurality Rule and the Best-Member Rule conditions. Since each block is composed of 8 trials, the frequency of cooperation (search and vote) during a block could range from 0 (a total free-rider) to 8 (a total cooperator). As can be seen in Figure 11, the relatively symmetric distribution pattern in the first block dissolved over time and the distribution in the last block was U-shaped, with the 100%-consistent

cooperators and 100% consistent free-riders jointly representing 32% (the Majority/Plurality Rule) and 42% (Best-Member Rule) of the participants. This indicates that, at least when individual adjustment is the basis for sorting into strategies, there is a trend towards polymorphic role self-assignment, with “types” of individuals adopting different consistent strategies.

Taken together, these results indicate that both uncooperative non-searcher/abstainer hybrids and cooperative searcher/voter hybrids persisted across trials, and that their proportions in each group stabilized over time.

INSERT FIGURE 11 – OBSERVED FREQUENCIES OF INDIVIDUAL STRATEGIES

Did the Majority/Plurality Rule outperform the Best-Member Rule?

Given that the rates of cooperation stabilized in each group over time, we can address our next question: Did the Majority/Plurality Rule produce better net benefits to group members than the Best-Member Rule? Figure 12 shows that average per-trial individual net benefits were higher in the Majority/Plurality Rule condition than in the Best-Member Rule condition across the three blocks of trials. A 2 (condition) x 3 (block) x 15 (group) repeated ANOVA using a Hierarchical Linear Model revealed a significant main effect for the group decision rule, $F(1, 28) = 11.90$, $p < .002$.

INSERT FIGURE 12 – MEAN INDIVIDUAL NET PAYOFFS

How does this pattern relate to the theoretical results from the evolutionary computer simulations? Notice that the theoretical equilibrium frequency of cooperators, estimated by fitting an econometric model to the data (Appendix B), was 1 in the Majority/Plurality Rule condition (see Figure 9). This means that, theoretically, the Majority/Plurality Rule should yield worse (at least no better) outcomes than the Best-Member Rule, because the minimal effective voting quorum for the Majority/Plurality Rule (three members) could not be assembled. However, as we observed in Figure 9, the mean frequencies of the cooperative, searcher/voter hybrids stabilized at slightly above three under the Majority/Plurality rule. The minimal quorum (three searcher/voter hybrids) persisted in the experiment and, consequently, the Majority/Plurality Rule yielded higher individual net payoffs than the Best-Member Rule (shown in Figure 12). These results imply that behaviorally—although not predicted by theory—the parametric range where the Majority/Plurality Rule outperforms the Best-Member Rule may be much wider than that predicted by theory (shown in Figure 7). Even in cases where individual cooperation cost is theoretically too high to secure the minimal quorum (three) for the Majority/Plurality Rule, observed frequencies of cooperators in each group often surpassed the quorum (Laury, Walker, & Williams, 1999; Sefton & Steinberg, 1996).

GENERAL DISCUSSION

The present research develops an explanation for the fact that human groups that engage in production often contain a share of highly cooperative individuals who contribute to public enterprises at a cost to themselves, such as those who prepare well for committee meetings, devote substantive time and energy writing a joint grant proposal, or stay on lookout to protect their village from enemies/predators. It provides a principled alternative to the over-generalized prediction of the linear model that the only rational choice is to free-ride. Recall that group production function in the linear model is often set arbitrarily by researchers. For example, it is common practice in public-goods game experiments to multiply an individual's contribution by some arbitrary number and then divide it by group size to determine a (constant) personal return from the contribution; and, this personal return is set to be less than the individual cooperation cost, regardless of the number of contributors in the group (Ledyard, 1995). Although such a linear model is a useful device to consider some theoretical problems concerning cooperation (e.g., effects of punishment; Fehr & Gächter, 2000), it is a serious misconception to assume that most natural group production tasks fall into this category. The analysis of the cooperate-or-free-ride, produce-or-scrounge decisions in terms of the Motro framework, with its plausible assumptions of a marginally-diminishing-returns group production function is conceptually compelling, realistic, and supported by theoretical simulations and a behavioral experiment. Our conceptual framework, based on the ubiquity of the marginally-diminishing returns group production function common

in natural settings, provides a useful benchmark explanation for realistic levels of cooperation in broad range of small group activities (McGrath, 1984; Steiner, 1972). It also seems more convincing than alternate, somewhat contrived explanations that posit special sources of indirect utility satisfaction such as “expressive functions” and utility derived from fulfilling “civic duty”, though these prosocial motives may be important in some cases (Brennan & Lomasky, 1993).

The insight that guides the present research is that group performance is not necessarily a strict social dilemma *if* group production is a marginally-diminishing function of the number of productive members (as it usually is) *and if* personal production costs add up (as they usually do). If the marginal individual return to contributing is greater than its cost for some members (i.e., $c < \delta_m$ for some m between 0 and group size), the equilibrium is a mixture of cooperation and free-riding. In simpler terms, in most groups it is to the individual member’s personal advantage to produce (contribute), unless an equilibrium number of other members is already contributing. We believe that group decision making tasks and many other group tasks in natural settings are of this type. Perhaps most surprising of all, we found that experimental human decision making groups yielded a stable behavioral equilibrium at a locally Pareto efficient level of public goods contributions, with 3 contributors and 3 free-riders per group. Finally, we found that majoritarian group decision rules have an adaptive value under uncertainty, and this result may explain why majority-plurality rules are popular across the full spectrum of human groups from hunter-gatherer or tribal societies (Boehm,

1996; Boyd & Richerson, 1985; Wilson, 1994) to modern industrial democracies (Hastie et al., 1983; Kameda et al., 2003; Mueller, 2003).

Our results are conceptually relevant to the long-term puzzle in political science about why citizens invest resources to become well-informed and to vote (e.g., Mueller, 2003; Riker & Ordeshook, 1973). In an election, the cost associated with voting is personal and seems to outweigh any individual benefit that the act of voting can possibly yield. Why would rational individuals bother to spend time and resources to become well-informed and go to the polls, if the chance of having an impact on the outcome of the election is virtually zero (“the Voter’s Paradox,” Downs, 1957)?

We should emphasize that there are several key differences between small-group decision making and elections. First, there is the obvious difference in the size of electorate, implying that each vote is much more consequential in small-group decision making than in a large-scale election. Second, most theoretical analyses of small-group decision making, including our own, have posited that “common values” (Feddersen & Pesendorfer, 1996) or “truth” (Condorcet, 1785/1994) underlie group decisions; members seek the mutually most beneficial outcome via group decisions (e.g., finding the most valuable investment, finding the truth in a criminal jury trial). In contrast, a large scale election is a competition among several factions (e.g., parties) with disparate ideologies and preferences. This difference is important because, in the political domain, two motives operate when each individual decides whether to vote or to not – free-riding and competition (Dhillon & Peralta, 2002; Palfrey & Rosenthal, 1983). Within each faction

(e.g., supporters of “Candidate A”) sharing the same preference, each individual is personally better off free-riding if a sufficient number of individuals are already voting for the alternative. However, in the political domain, competition is also a motive. In order for your party to win the election, you must assemble more voters than the other parties. This competition factor is absent in our group decision making situation where members collectively play a “game against nature” (Bornstein, 2003).

In this sense, it remains to be seen how exactly the two decision situations relate to each other, both theoretically and behaviorally. One possible extension of our group decision-making paradigm might be to have two teams of hunters compete for the same resource. The team with the more accurate group decision monopolizes the resource and distributes it evenly among members on the winning team, as found in some political domains. How cooperative will members be in situations where the competitive and free-riding motives conflict? Will a stable equilibrium emerge over time? Is the Majority/Plurality Rule better in those settings than the Best-Member Rule? These questions are important and provide another test of the adaptive robustness of majoritarian decision making under uncertainty.

There are several limitations on the conclusions of this paper. Perhaps most obvious is the assumption that group members develop individual judgments independently from each other. Although this assumption has been common in the previous theoretical work (Hastie & Kameda, 2005; Sorkin et al., 2001), future work should relax this condition to see its impact on group decisions. Indeed, if members

conform (Asch, 1956) or mimic (Hung & Plott, 2001) each other when forming individual judgments, majoritarian aggregation could be subject to “herding” effects, where erroneous information cascades across individuals to yield defective outcomes (e.g., Anderson & Holt, 1997; Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992; Kameda & Tamura, 2007). Because the Majority/Plurality Rule works under uncertainty via its error-cancellation function (Hastie & Kameda, 2005; Hung & Plott, 2001), independence among members is a key contributor to its success (Surowiecki, 2004). One possible extension to address this question is to provide each individual (computer agent or human participant) an option to mimic another’s judgments (i.e., free-riders who skip information search can mimic other members, rather than deciding randomly as assumed in the current model) and to examine the performance of the majoritarian aggregation when social learning is possible (Henrich & Boyd, 1999; Kameda & Nakanishi, 2002, 2003).

Second, our results are obviously contingent on the distribution of competence among group members. In the simulation, group members’ modal judgment policies were not statistically optimal (Eq. 1) but were based on the suboptimal, “equal cue-weighting” (Dawes, 1979) with substantive variation; members’ preferences were thus affected not only by random error in cue perception but also by the systematic biases built in their judgment policies. However, if these modal members had even more deviating judgment policies while the most competent member had a near perfect judgment policy, then the parametric range where the Majority/Plurality Rule

outperforms the Best-Member Rule would necessarily become much narrower (Kerr et al., 1996). It remains to be seen how and under what conditions the accuracy of modal group members' preferences, relative to that of the brightest member, can be guaranteed in naturally-occurring settings (Surowiecki, 2004).

Third, in our simulation and experiment, group members had no direct opportunities to coordinate their actions *ex ante*. However, if members are allowed to coordinate their behaviors in advance, they may eventually develop some social norms to produce more equitable outcomes within a group, rather than allowing some members to free ride on others unilaterally (Figure 11). For example, such social norms may take the form of turn-taking to bear the cost of cooperation equally among all members. Given the central importance of "inequity aversion" in human cooperation (Fehr & Schmidt, 1999), it will be interesting to see how such egalitarian norms and mutual expectations (Fehr & Fischbacher, 2004; Kameda, Takezawa, Ohtsubo & Hastie, 2010; Kerr, 1983) may develop in groups working on tasks with marginally-diminishing-return-curves.

Lastly, the model we have developed in this paper is an evolutionary/population-level model whereby ultimate causes (Tinbergen, 1963) for cooperation in group decision making are considered. It still remains to see how each individual actually computes costs and benefits of their cooperation in a group task with a marginally-diminishing-return-curve, and especially how they coordinate their behaviors. Behavioral ecologists studying group decision making by non-human animals have

begun to address these questions to understand computational algorithms for collective nest search by honey bees, collective navigation by baboons, and so on (see the special issue of *Philosophical Transactions of the Royal Society B*, 2009, edited by Larissa Conradt and Christian List). Given the robustness of marginally-diminishing-returns group production function in nature (Foster, 2004), cross-fertilization between human and non-human animal researchers will be useful to delineate proximate mechanisms underlying cooperation and coordination in group endeavors.

We hope our methodology, starting with a description of the situation in game theory terms, followed by computer simulation explorations, and then behavioral experiments is appealing to other researchers. And, we hope that the virtues of this eclectic approach are self-evident. Social behavior is often more adaptive and more rational than it sometimes appears at first glance. Thinking about functional, adaptive, and rational properties of a system will often reveal a deeper structure that is not apparent to a superficial descriptive analysis (Barkow, Cosmides & Tooby, 1992; Gigerenzer et al., 1999; Schelling, 1978). The wisdom of crowds can arise from fundamental laws of social ecology that emerge from individually adaptive strategies (Surowiecki, 2004).

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Table 1. Four behavioral strategies implemented in the evolutionary simulation

		Participate in group meetings?	
		Yes	No
Engage in individual information search?	Yes	Searcher/Voter	Searcher/Abstainer
	No	Non-searcher/Voter	Non-searcher/Abstainer

Appendix A

Implementation of the replicator dynamic in the evolutionary computer simulation

We used the following formula to represent the selection process (Henrich & Boyd, 1998). Let us denote proportion of strategy i ($= 1$ or 2) in the population at generation t as p_i^t , and its fitness outcome as O_i^t . Then its proportion in the population at generation $t+1$ is:

$$p_i^{t+1} = \frac{p_i^t (W + O_i^t)}{\bar{W}_t},$$

where W is the baseline-fitness constant which is common to all strategies (we set $W=30$ in the current simulation), and \bar{W}_t is the average fitness outcome:

$$\bar{W}_t = \sum_i p_i^t (W + O_i^t).$$

Appendix B

Estimation of the empirical group and individual payoff functions

We describe a simple model in which the group's aggregate payoff as a function of the number of group members who contribute information has diminishing marginal returns. For analytic tractability, we make standard assumptions that result in an objective function that rewards predictive accuracy by providing a fixed reward from which the squared error of the group's prediction is deducted. Accurate predictions have smaller squared errors and consequently higher payoffs according to this objective function. *A priori*, errors can be expected but are not known until *ex post* values of all random variables are realized. It is straightforward to show that the resulting expected payoff function is increasing in the quantity of information, but concave, implying diminishing marginal returns to information.

Consider a group trying to predict the unknown outcome x . Denote its forecast m . The group receives (in the aggregate) a fixed payoff B if its forecast is perfectly accurate (i.e., $m = x$). The group's payoff, however, decreases as the group's squared prediction error grows larger. Denoting the scaling of squared errors into the units used in the payoff function as λ , we can assemble the symbols defined above to form the group's (aggregate) gross payoff function:

$$\text{gross group payoff} = B - \lambda (m - x)^2.$$

Let N denote the number of noisy pieces of information that the group forecast depends on, so that the functional notation $m(N)$ describes the mapping from quantity of

information into group forecasts. Denoting the cost of information as p per unit, then the net group payoff function becomes:

$$\text{net group payoff} = B - \lambda (m(N) - x)^2 - pN.$$

In general, the best use of N noisy signals, $(x + \varepsilon_1), \dots, (x + \varepsilon_N)$, is to construct the forecast $m(N)$ as the conditional expectation of x , which is very often assumed to take a linear form:

$$E[x | \varepsilon_1, \dots, \varepsilon_N] = \alpha + \beta_1(x + \varepsilon_1) + \dots + \beta_N(x + \varepsilon_N).$$

A simpler and more robust approach (in the absence of enough stability in the environment to estimate the parameters in the regression) would be the simple average:

$$m(N) = \sum_{i=1}^N (x + \varepsilon_i) / N = x + (\varepsilon_1 + \varepsilon_2 + \dots + \varepsilon_N) / N.$$

We now compute the expected value of the net group payoff function:

$$\begin{aligned} E[B - \lambda (m - x)^2 - pN] &= B - \lambda E[(\varepsilon_1 + \varepsilon_2 + \dots + \varepsilon_N)^2] / N - pN \\ &= B - \lambda \sigma_\varepsilon^2 / N - pN. \end{aligned}$$

Applying this function as the group's expected net payoff function, we can examine the individual-level incentives for a single member of this group who is facing a binary decision of whether to pay p and provide one more noisy signal to be included in the group's forecast, or to free-ride on the information acquisition of others. We assume, as everywhere else in this paper, that gross group payoffs are divided evenly among all group members (cooperators and free-riders alike) but the costs of information are borne individually. Thus, if there are n other group members cooperating in a group with M members in total, after netting out costs for the cooperator, the individual's expected net payoff is:

Expected net individual payoff for a cooperator = $(1/M)(B - \lambda \sigma_\varepsilon^2 / (n+1)) - p$,

Expected net individual payoff for a free-rider = $(1/M)(B - \lambda \sigma_\varepsilon^2 / n)$.

The point at which the individual payoff curves intersect defines the so-called Nash point (see footnote 10):

$$n^* = -0.5 + 0.5[1 + 4 \lambda \sigma_\varepsilon^2 / (pM)]^{0.5}.$$

At integer values to the left of n^* , the strategy of cooperation maximizes individual payoffs even though some other members are free-riding. At integer values to the right of n^* , free-riding maximizes individual payoffs. As intuition would suggest, n^* is a decreasing function of the price of information, p , holding all else equal. Also, n^* is increasing in λ , because higher penalties for forecasting error increase the individual rationale for contributing information. Similarly, n^* is increasing in σ_ε^2 , because, when each single piece of information is lower in quality (i.e., less precise), the marginal returns from additional units of information diminish less rapidly, implying a rightward shift in the cooperator-free-rider cross-over point. Finally, holding all else equal, n^* is decreasing in group size. The incentive to cooperate is present for fewer group members, the larger the group is.

Recall that the expected aggregate net payoff function for the group is:

$$\text{Expected aggregate net payoff} = B - \lambda \sigma_\varepsilon^2 / N - pN.$$

We refer to the total number of cooperators N that maximizes the expected aggregate net payoff as the Pareto point and denote this special value of N as N^* (see footnote 10):

$$N^* = (\lambda \sigma_\varepsilon^2 / p)^{0.5}.$$

Notice that the Pareto point is independent from the parameters B and M . It depends

positively on the penalty for forecast error and on the imprecision of private information, and is decreasing in the price of information.

This model is used to estimate the empirical group and individual payoff functions in the body of the paper. The estimation procedure is as follows. First, we estimate the gross individual payoff conditional on the reciprocal of the total number of cooperators in each group, $1/N$. The notation introduced here uses subscripts g to index groups and t to index experimental trials. Because gross payoffs (before netting out the cost of individual information acquisition) are the same for all group members, the notation here does not index individuals' identities, although this is straightforward to add. Using the definitions from above, any individual in group g receives an individual gross payoff in trial t given by the following expression

$$\text{individual's gross payoff} = E[y_{gt} | 1/N_{gt}] = (1/M)(B - \lambda \sigma_\varepsilon^2 / N_{gt}),$$

where g ranges from 1 to 15, and t ranges from 1 to 72, for a total of $15 \times 72 = 1080$ observations that are obviously not statistically independent. Because the same group is observed 72 times, the statistical model allows for within-group correlation of the 72 error terms in the regression model, which affects the size of estimated standard errors but not the estimated coefficients. There were only three observations in which $N = 0$. The model is valid only when $N > 0$, and therefore the regression coefficients were estimated using the 1077 observations for which N ranged between 1 and 6. This produced statistically significant regression coefficients, and the following estimated regression line where coefficients are rounded to the nearest integer:

$$E[y | 1/N] = a + b (1/N) = 60 - 9/N.$$

This regression line is plotted in Appendix-Figure 1 together with mean values of y at each value of N , the total number of cooperators in the group. It is straightforward to estimate expected individual net payoff for a cooperator and for a free-rider as a function of n , the number of *other* group members who cooperate, from Appendix-Figure 1. For a free-rider, there are no costs to net out, and the gross individual payoff in Appendix-Figure 1 is identical to the net payoff, plotted as a dashed line in Appendix-Figure 2. For a free-rider, the total number of cooperators in the group is equal to the number of other group members cooperating: $N = n$. For a cooperator, however, the total number of cooperators includes the others plus him or herself, and therefore $N = n + 1$, plotted in Appendix-Figure 2 as the solid line after subtracting 6 yen for the cost of contributing to the public good. The figure shows that the two payoff curves cross strictly to the left of $n=1$, where n represents the number of other group members who cooperate. This implies that cooperation maximizes individual payoffs when no other group members cooperate (at $n = 0$), and free-riding maximizes individual payoffs as soon as there is at least one other group member cooperating (when $n > 0$). Thus, any Nash equilibrium is a profile of binary actions in which there is one cooperator and five free-riders.

 INSERT APPENDIX-FIGURES 1 & 2

Appendix-Figure 3 shows the empirical net aggregate payoff for groups as a

function of the total number of cooperators. The points on this curve are empirical averages over 1080 observations of group payoffs and numbers of cooperators. The curve has a local maximum at 3 and a global maximum at 6. Thus, three is a local Pareto point, although a benevolent dictator aiming to maximize aggregate payoffs would choose the global Pareto point, 6.

 INSERT APPENDIX-FIGURE 3

In linear public goods games, the dominant strategy is usually to contribute zero and, if not zero, then the other boundary point of the action space (i.e., contributing the maximum amount). In contrast, nonlinear public goods payoff structures can generate Nash equilibria on the strict interior of the agents' action spaces. Our model's Nash equilibrium requires 1 contributor per group, which falls short of the socially efficient Pareto points of 3 (local) and 6 (global) contributors per group. As shown in Figure 10, the data revealed a pronounced mode at 3 and showed that the groups we observed regularly achieve larger aggregate payoffs than the Nash equilibrium predicts. We found that groups stably functioned at a locally Pareto efficient level of public goods contributions, with 3 contributors and 3 free-riders per group. The unambiguous modal value is remarkable, in that subjects find a locally best social outcome as a group that requires asymmetric action profiles among group members, without any mechanism to coordinate action. The subjects in our study earn more by cooperating more than is

predicted from the individual incentives built into the game structure.

Figure Captions

Figure 1. An illustration of a marginally-diminishing return curve (unit here is arbitrary) as a function of number of cooperators. The y-axis has been adjusted to expected gross return to each individual (group gross return / 6). An ESS is defined as follows (Motro, 1991): Cooperate as long as the marginal increment (δ) exceeds individual cost (c), but switch to defection beyond that.

Figure 2. Expected individual net payoffs (individual gross return – cost) for a cooperator (solid curve) and a defector (dashed curve), as a function of the number of other members who cooperate (derived from the gross return curve in Figure 1 with individual cooperation cost fixed at 0.7).

Figure 3. Structure of the simulated judgment environment

Figure 4. Outline of the evolutionary simulation platform

Figure 5. Equilibrium proportions of the strategies in each population

Figure 6. Individual net payoff at the equilibrium in each population

Figure 7. Sensitivity analysis about the superiority of Majority/Plurality Rule to the Best-Member Rule in individual net payoff

Figure 8. Interlocking between the two strategic choices. Participant's behavioral choices of information search strategy and voting became more coherent over time.

Figure 9. Mean frequencies of cooperative members (searcher/voter hybrids) across the 24 trials. Vertical lines indicate one standard error (solid line for the Majority/Plurality Rule condition, and dotted line for the Best-Member Rule condition). Empirically-estimated Nash point in the Majority/Plurality Rule condition was 1, whereas Pareto optimal points were 3 (local Pareto optimal) and 6 (global Pareto optimal). See Appendix B for details of the estimation procedure.

Figure 10. Frequency distribution of number of cooperators (searcher/voter hybrids) in groups in the Majority/Plurality Rule condition across 360 observations (15 groups in 24 trials).

Figure 11. Observed frequencies of individual strategies in the Majority/Plurality Rule condition and the Best-Member Rule condition. Individual strategies could range from full defection (0) to full cooperation (8) in each block of trials.

Figure 12. Mean per-trial individual net payoffs (in Yen) in the Majority/Plurality Rule condition and the Best-Member Rule condition.

Appendix-Figure 1. Fitted regression line for individual gross payoffs (and observed means) as a function of N , the total number of cooperators in the group. The regression model is $E[\text{individual gross payoff} \mid 1/N] = a + b(1/N) = 60 - 9/N$, for $1 \leq N \leq 6$. The mean of three payoff observations for $N = 0$ is plotted in the figure as well, although it is not derived from the regression model with the restricted range of N . The model was fit with 1077 observations, and the coefficients were statistically significant at the 5% level.

Appendix-Figure 2. Estimated net individual payoffs for cooperators (solid line) and free-riders (dotted line) as a function of the number of other cooperators in the group.

Appendix-Figure 3. Empirical net aggregate payoff for groups as a function of N , the total number of cooperators in the group (summing over 6 group members' individual payoffs after netting out costs for cooperation). The curve has a local maximum at 3 and a global maximum at 6. Thus, three is a local Pareto point, although a benevolent dictator aiming to maximize aggregate payoffs would choose the global Pareto point, 6.

Footnotes

¹ Laury and Holt (2008) provides a survey on the economics literature regarding nonlinear public goods games. To understand the motivation that has led economists to study nonlinear public goods games, which is very different from the present study's motivation, it is helpful to recall that the standard linear public good game most frequently studied in laboratory experiments has a unique Nash equilibrium in which all group members contribute zero. Thus, the theoretical model upon which most public goods experiments are based predicts universal and absolute free riding. In contrast with this theoretical prediction, participants in experiments usually contribute significantly more than zero. These contributions typically decline with repeated trials, but contributions remain well above zero even after as many as 60 rounds. Interpreting this frequently replicated finding of greater than zero contributions in linear public goods games remains difficult, however, because of the statistical difficulty of measuring closeness to a boundary in any action space (in this case, the zero-contribution Nash equilibrium). At a boundary point in participants' action space, deviations can occur only in one direction; random error of any kind will push empirical averages away from their true value and the law of large numbers no longer holds. Faced with this statistical problem of measuring deviations from an equilibrium located at the boundary of the range of individual contributions, economists turned to nonlinear public goods games as a mechanism for generating incentive structures with Nash equilibria located on the "strict interior" ($0 < \text{equilibrium frequency} < \text{group size}$) of the

range of possible contributions. This is the primary motivation for most of the existing experimental economics literature on nonlinear public goods (see Laury and Holt, 2008). In contrast, this paper reconsiders nonlinear public goods incentive structures as a widespread empirical regularity and investigates what insights they have to offer to psychology and the neighboring social science literatures dealing with social dilemmas, information acquisition, and voting behavior, concerning the commonplace observation of heterogeneous groups consisting of both cooperators and free-riders.

² In game theory, an evolutionarily stable strategy is a strategy that if adopted by all players in a population cannot be invaded (outperformed) by any competing alternative strategy (Maynard Smith, 1982; Gintis, 2000). Suppose a situation in which a group is composed only of individuals with the focal strategy, x . Now a question arises concerning if such an all- x group is robust enough to block a small number of individuals with another strategy (y) from intruding into the group. Does strategy x outperform strategy y in terms of average profit? If strategy x actually outperforms strategy y , it can block y 's intrusion into the group, analogous to biological "competition" for an ecological niche. If strategy x is dominant in this sense over all other strategies in the game, then strategy x is called an Evolutionarily Stable Strategy (ESS).

³ Notice that, different from the behavioral strategies, no game-theoretic aspect is involved in member's judgment policy. The theoretically best judgment policy always corresponds to the optimal linear combination model (e.g., Eq. 1), which is solely determined by the environmental structure, independent of other members' judgment

policies in a group. In other words, a member's judgment policy is not a strategy in the game-theoretic sense. Thus, after being randomly generated for each group member at the outset (see the text), the judgment policy was fixed and not under evolutionary control throughout a simulation run. Elsewhere, we have discussed how such cognitive differences can affect qualities of group decisions under different aggregation rules (see Hastie and Kameda, 2005 for details).

⁴ To illustrate, let us suppose that a group picked up a location with 36 resource units, where value of resource available at each of 10 locations had been generated randomly from $N(0, 30)$. Because each member of the 12-person group receives an equal share, this yields 3 resource units per person, which means that the total cost for cooperation to be subtracted from a cooperator's share, 0.03, corresponds to 1% of the gross individual payoff.

⁵ $N(80, 30)$ was used to generate resource levels in each location in the experiment, instead of $N(0, 30)$ in the simulation; the change in mean value does not affect uncertainty level in the foraging task because the standard deviation of the distribution was held identical. The only exception was that both the true resource value (Q_j) and the true cue value (C_{jk}) in each of 72 hunts during the experiment were held to be common across all groups in the experiment. These common "seeds" had been generated randomly from the respective normal distributions (identical to those used in the simulation), for once, prior to the experiment. This procedure was different from the simulation, where the true resource value (Q_j) and the true cue value (C_{jk}) were

generated randomly for each hunt by each group. Given the much smaller sample size in the experiment ($n = 3$ hunts * 15 groups per trial as compared to $n = 100$ hunts * 10,000 groups per generation in the simulation), making the value-generation procedure exactly parallel to that of the simulation would introduce too much random noise. Because this change is theoretically trivial, we chose the current procedure for the experiment. For each hunt by each group, however, we newly added individual perception error terms (e_{ijk}) to generate perceived cue values (C_{ijk}) as in the simulation. Thus, the cue values that participants actually observed in each hunt could be different from person to person.

⁶ The total cost for cooperation (information search + voting) implemented in the experiment (6 yen per trial) may seem small. Yet, this was not the case because, as seen in Figure 12, it actually corresponded to about 10% of the average gross payoff to each individual in the trial (see Figure 12).

⁷ Our own experience tells us that it is hard to tell whether other members have actually prepared for committee meetings (e.g., engaged in costly information search), thus the number of searchers during the trial was not included in the outcome feedback.

⁸ It is important to note that the simulation and the behavioral tests involved different manifestations of what we think are the same basic principles of functional adaptation. In the simulation, an evolutionary algorithm determined the surviving strategies over thousands of generations using a replicator dynamic. However, in the behavioral experiment, individual learning and inference processes composed the mechanism

through which an adaptive equilibrium was discovered. We believe that both routes, population cross-generational and individual learning, yield adaptive behavioral strategies, but we do not want to obscure the differences between the two mechanisms (but see Campbell, 1988).

⁹ The equilibrium (Nash) frequency occurs where the marginal individual return is equal to the cost of cooperation (Figures 1 & 2; see also Appendix-Figures 1 & 2). The Pareto-optimum frequency occurs where the marginal group return is equal to the cost of cooperation; net group payoff function is maximized at the Pareto point. In the econometric analysis reported in Appendix B, we estimated the equilibrium (Nash) frequency and the Pareto-optimum frequency. As shown in Appendix-Figure 3, the empirical net group payoff function reveals two Pareto-optimal points, a local maximum where the number of cooperators in the group is 3, and a global maximum at 6. At each of these Pareto points, net group payoff is maximized locally or globally.

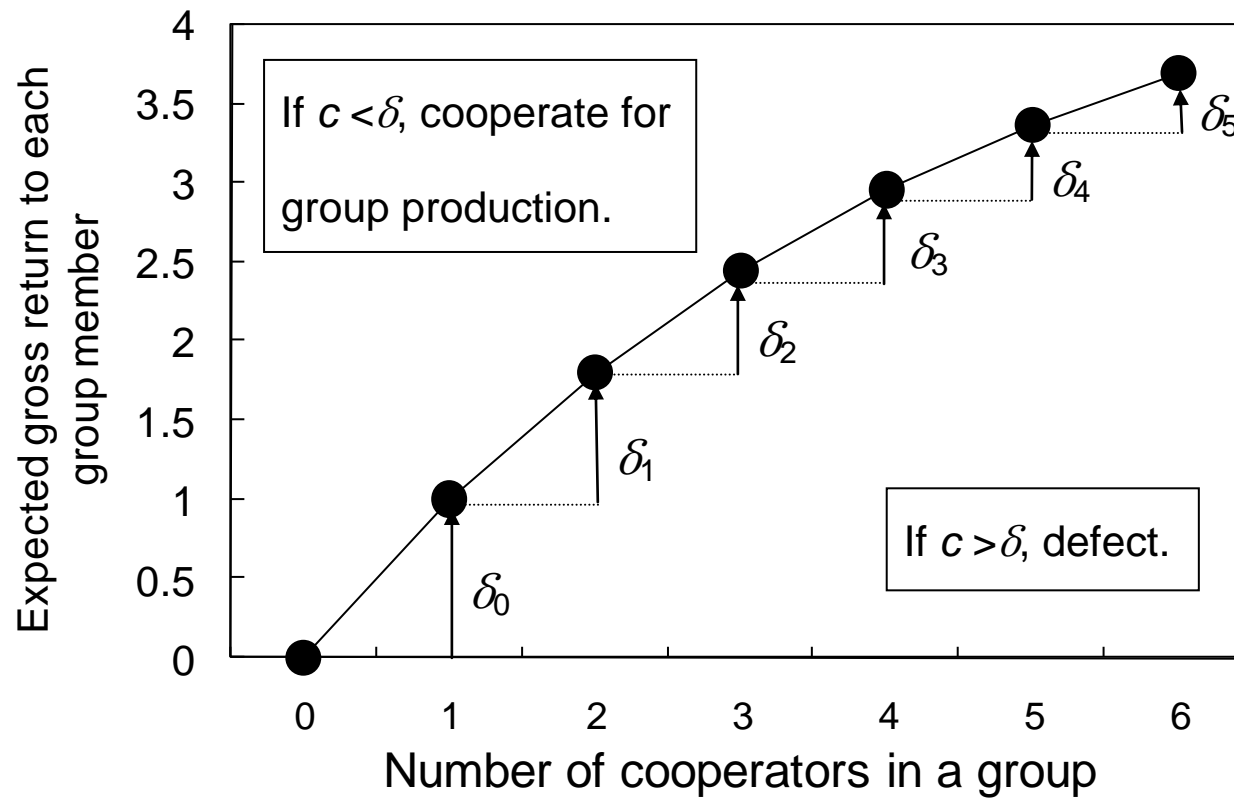


Figure 1. An illustration of a marginally-diminishing return curve (unit here is arbitrary) as a function of number of cooperators. The y-axis has been adjusted to expected gross return to each individual (group gross return / 6). An ESS is defined as follows (Motro, 1991): Cooperate as long as the marginal increment (δ) exceeds individual cost (c), but switch to defection beyond that.

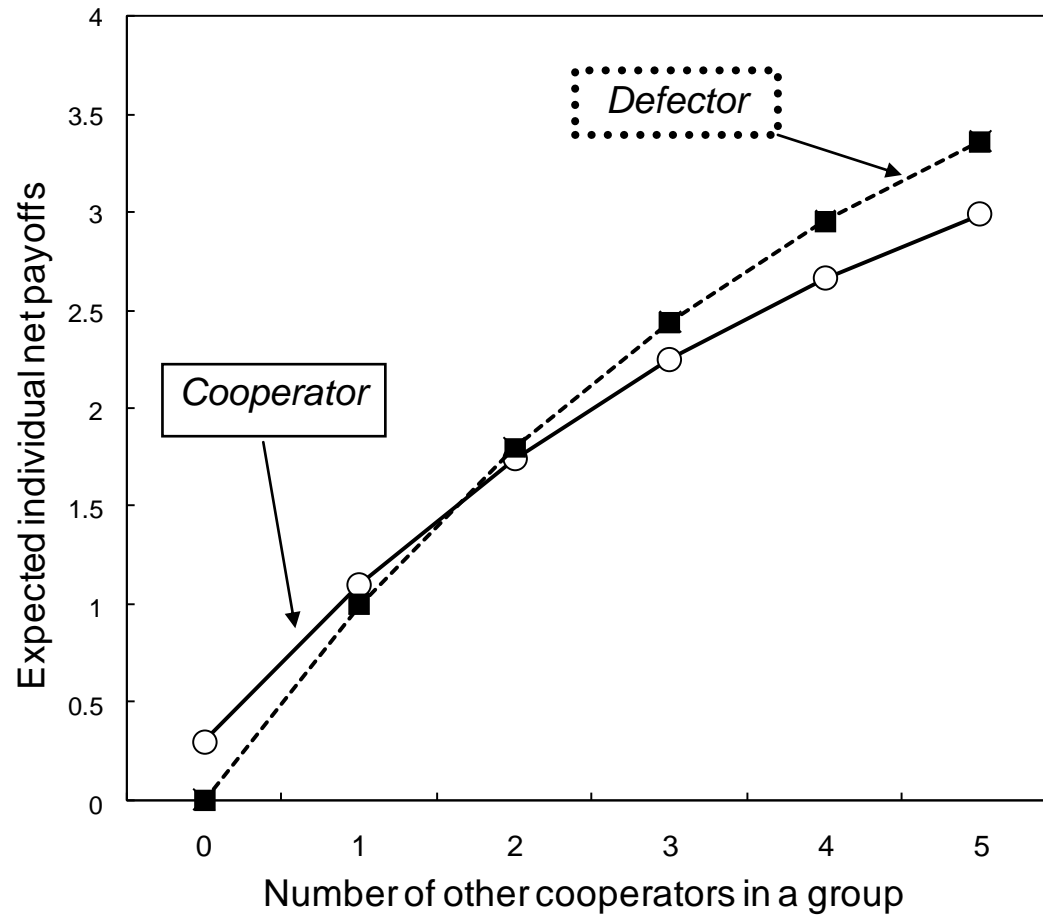


Figure 2. Expected individual net payoffs (individual gross return – cost) for a cooperator (solid curve) and a defector (dashed curve), as functions of the number of other members who cooperate (derived from the gross return curve in Figure 1 with individual cooperation cost fixed at 0.7).

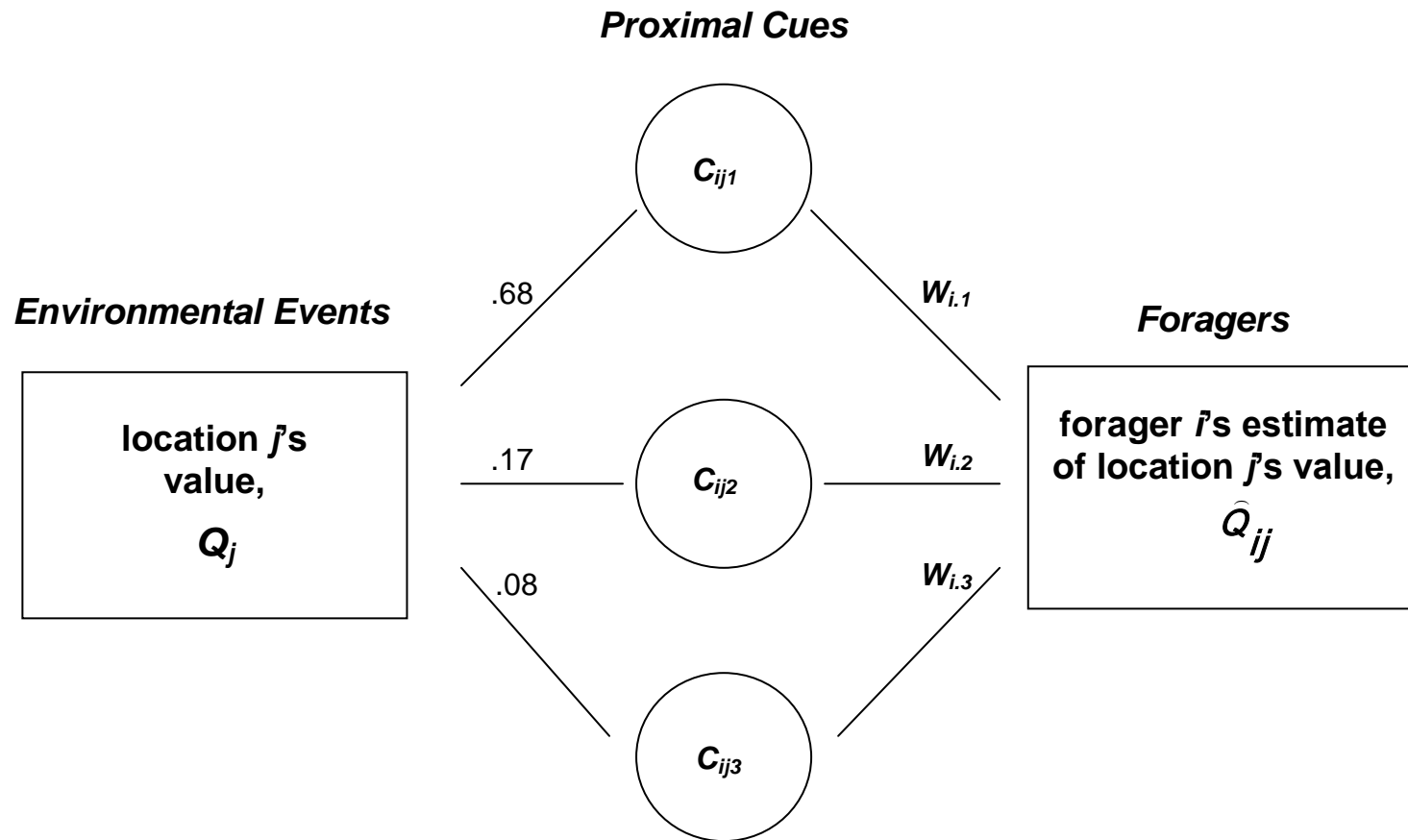


Figure 3. Structure of the simulated judgment environment

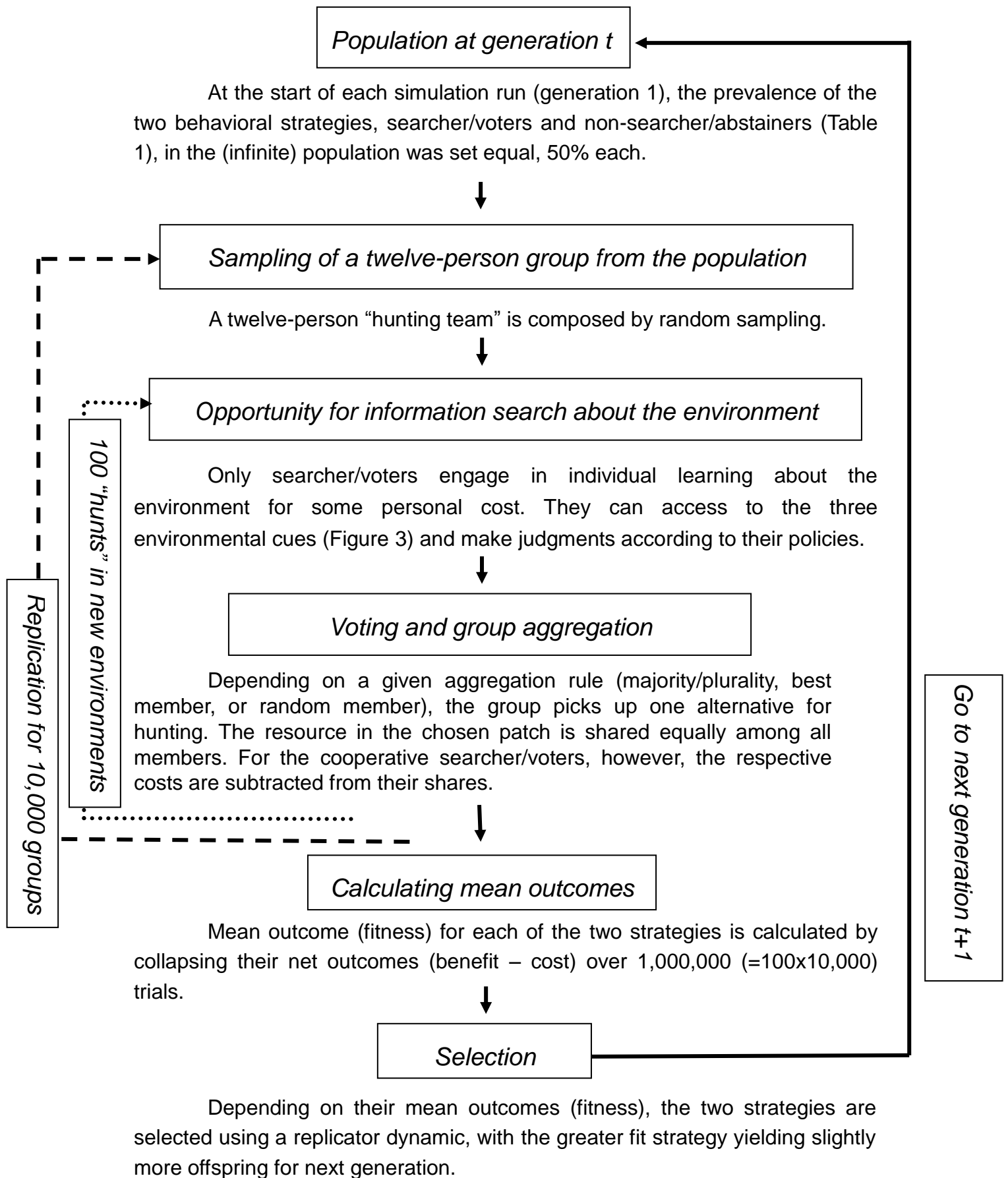


Figure 4. Outline of the evolutionary algorithm

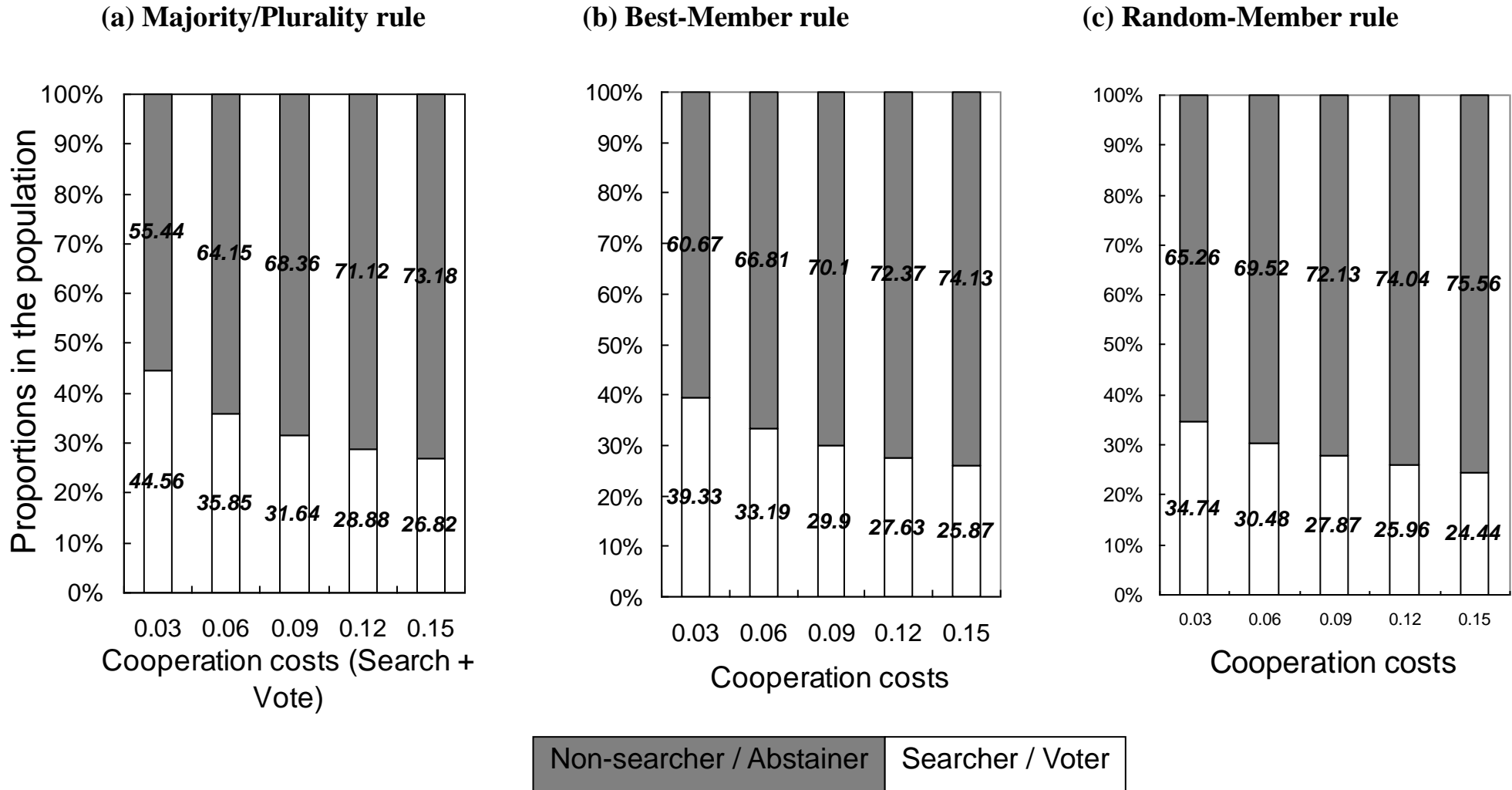


Figure 5. Equilibrium proportions of the strategies in each population

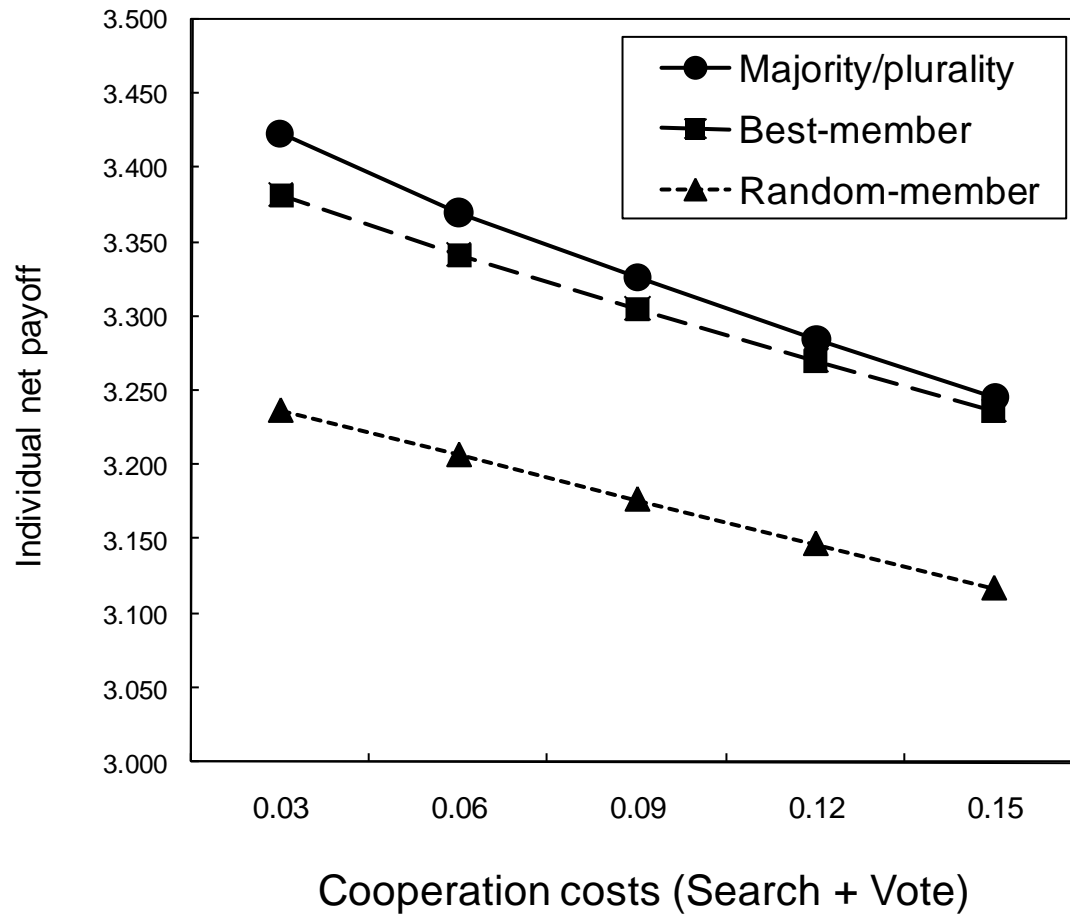


Figure 6. Individual net payoff at the equilibrium in each population

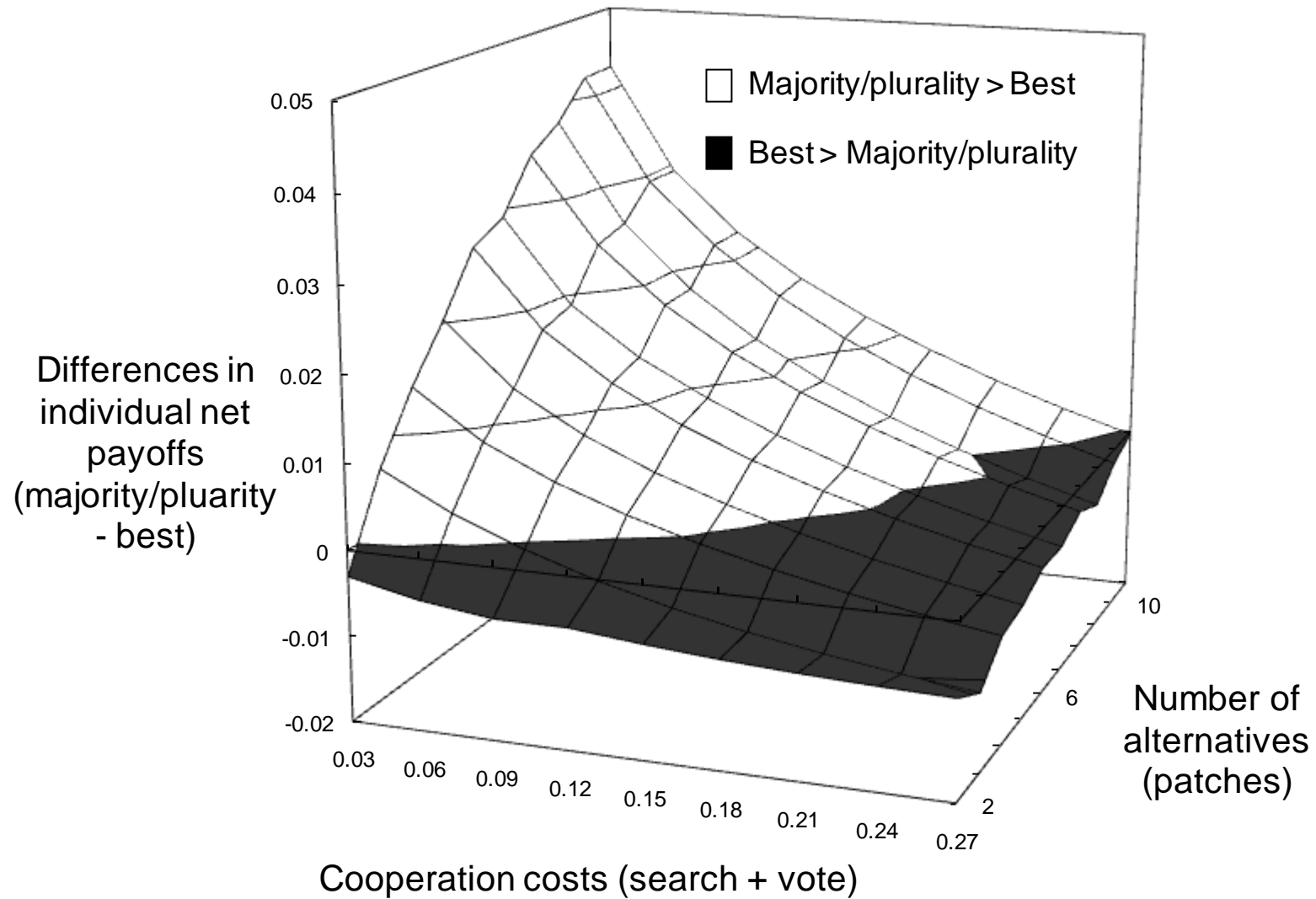


Figure 7. Sensitivity analysis about the superiority of Majority/Plurality Rule to the Best Member Rule in individual net payoff

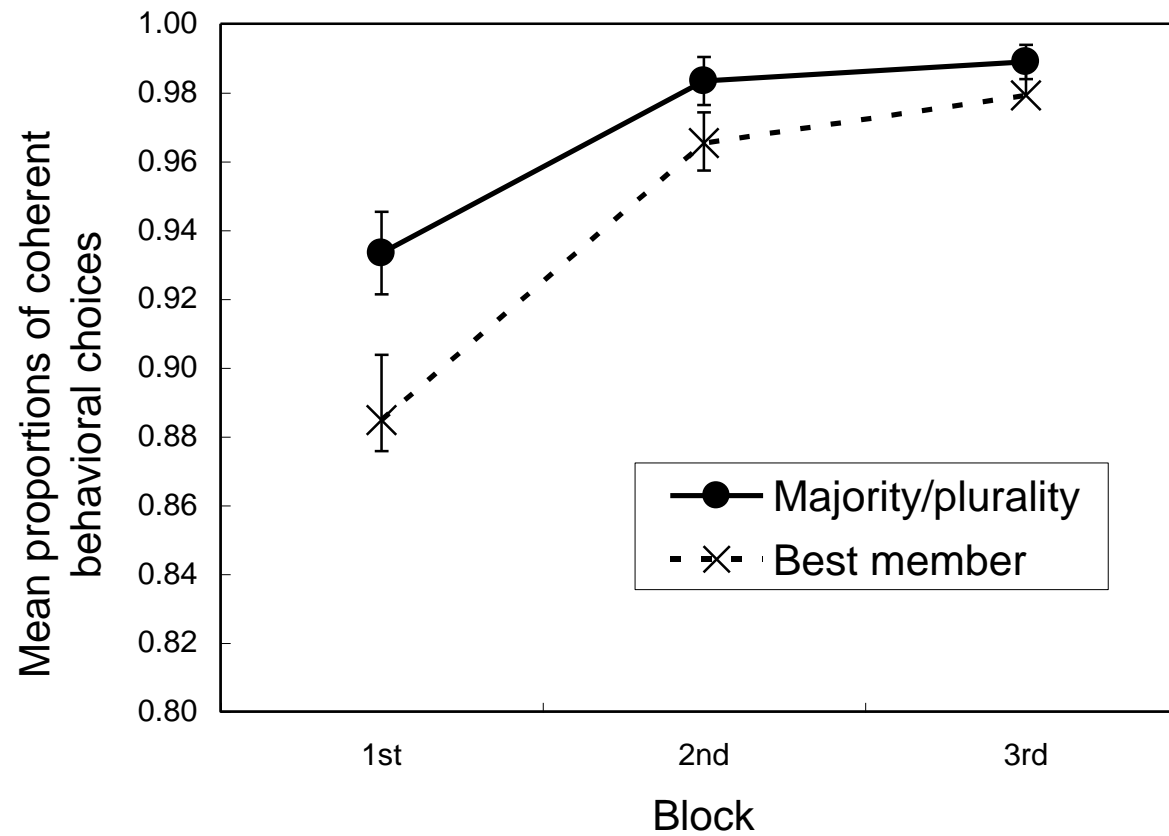


Figure 8. Interlocking between the two strategic choices. Participant's behavioral choices of information search strategy and voting became more coherent over time.

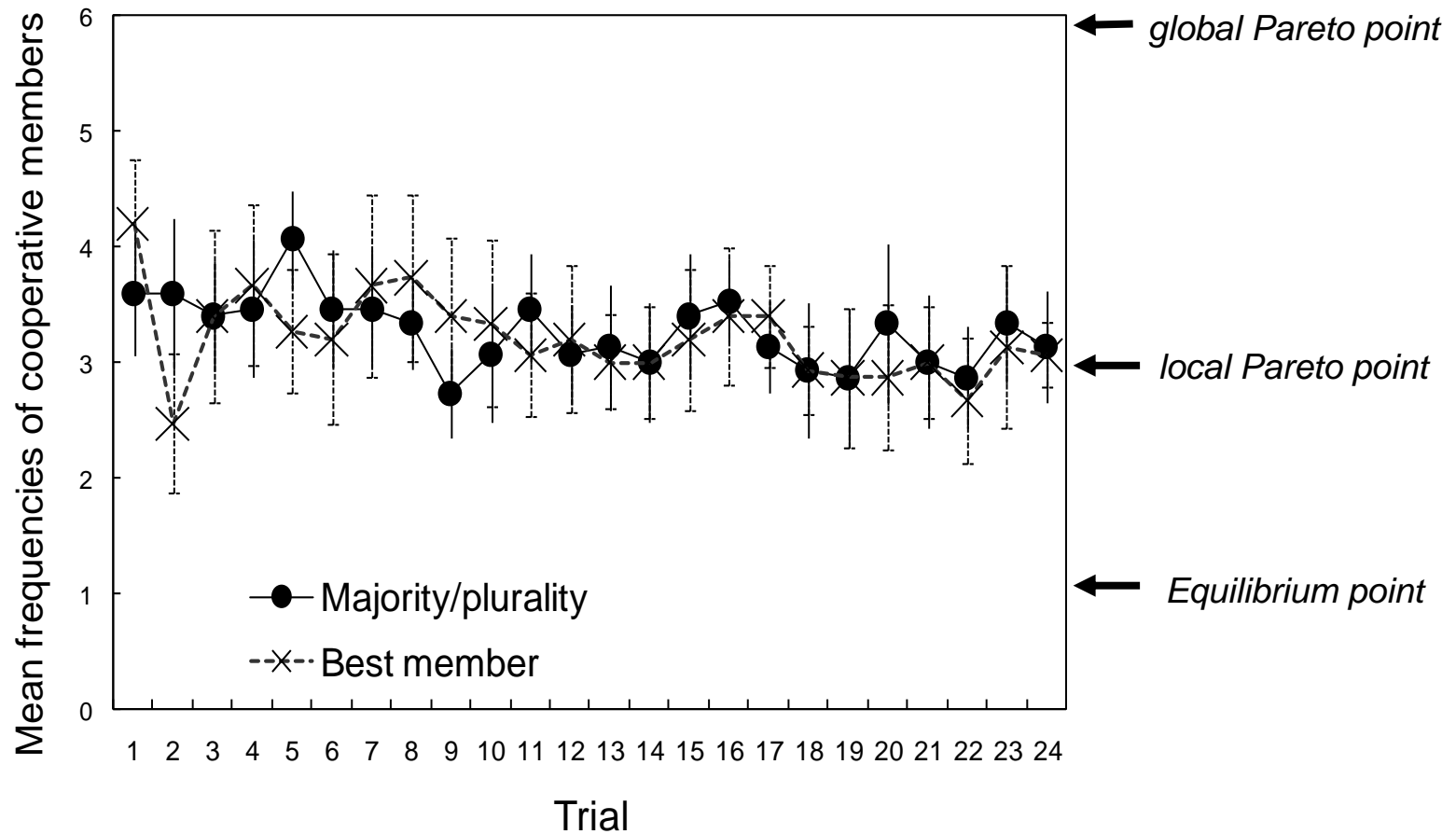


Figure 9. Mean frequencies of cooperative members (searcher/voter hybrids) across the 24 trials. Vertical lines indicate one standard error (solid line for the Majority/Plurality Rule condition, and dotted line for the Best Member Rule condition). Empirically-estimated equilibrium point in the Majority/Plurality Rule condition was 1, whereas Pareto optimal points were 3 (local Pareto optimal) and 6 (global Pareto optimal). See Appendix B for details of the estimation procedure.

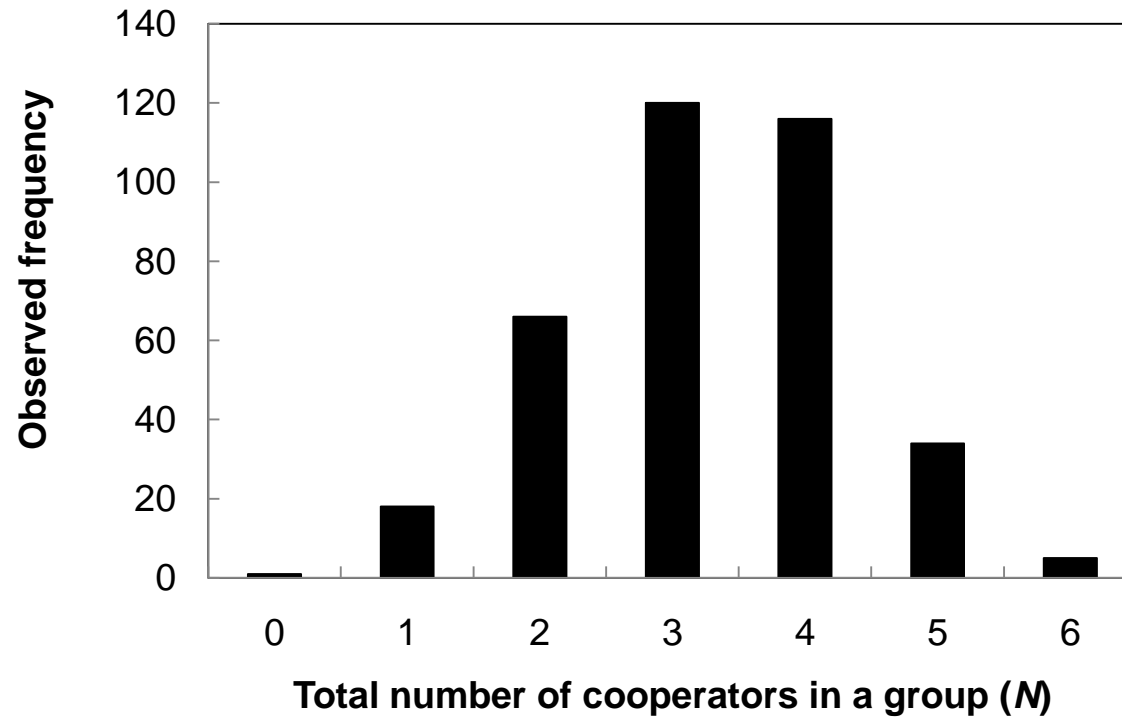


Figure 10. Frequency distribution of number of cooperators (searcher/voter hybrids) in groups in the Majority/Plurality Rule condition across 360 observations (15 groups in 24 trials).

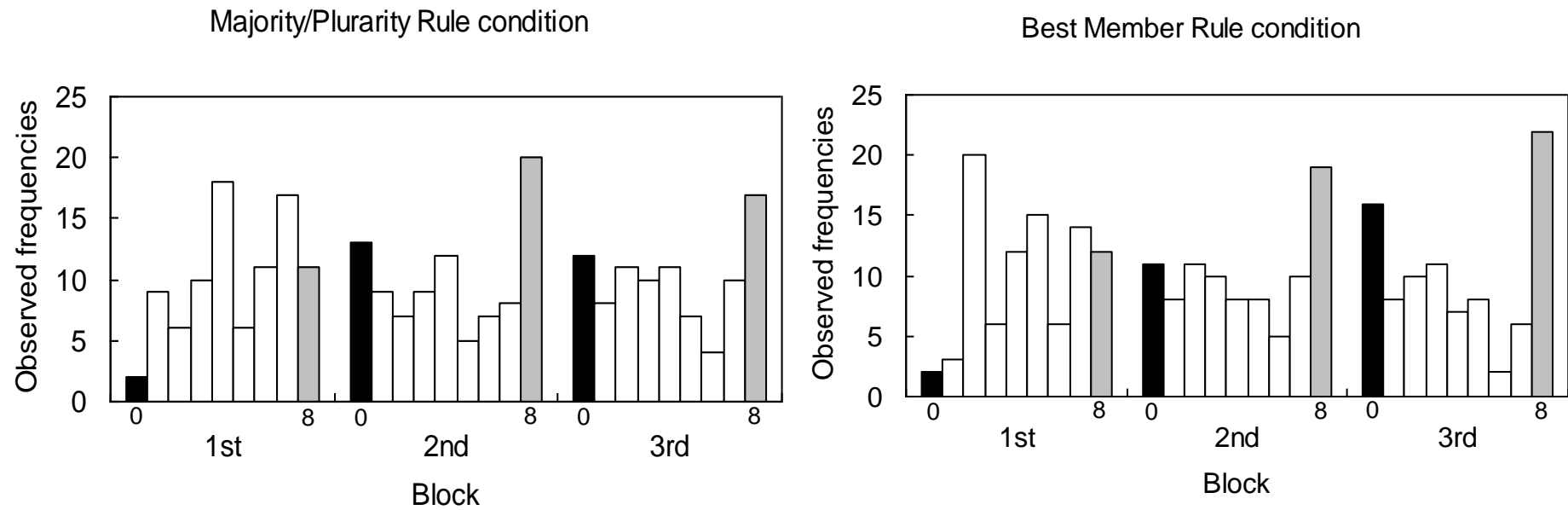


Figure 11. Observed frequencies of individual strategies in the Majority/Plurality Rule condition and the Best Member Rule condition. Individual strategies could range from full defection (0) to full cooperation (8) in each block of trials.

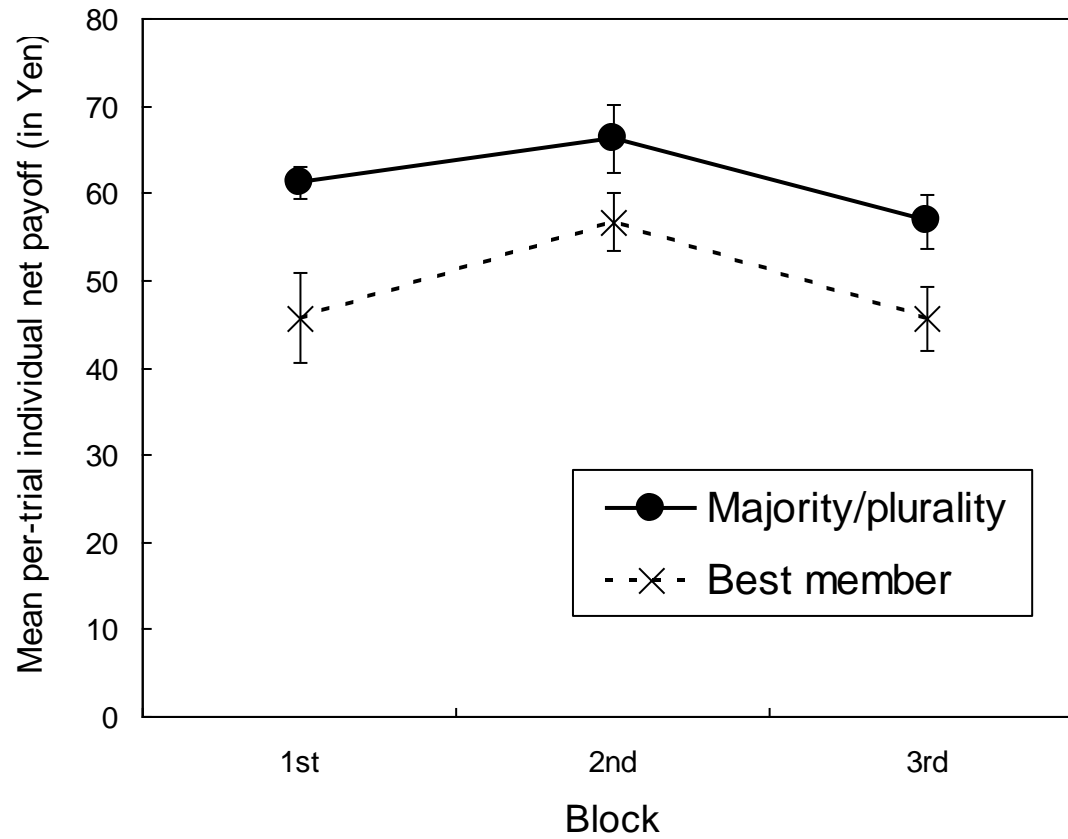
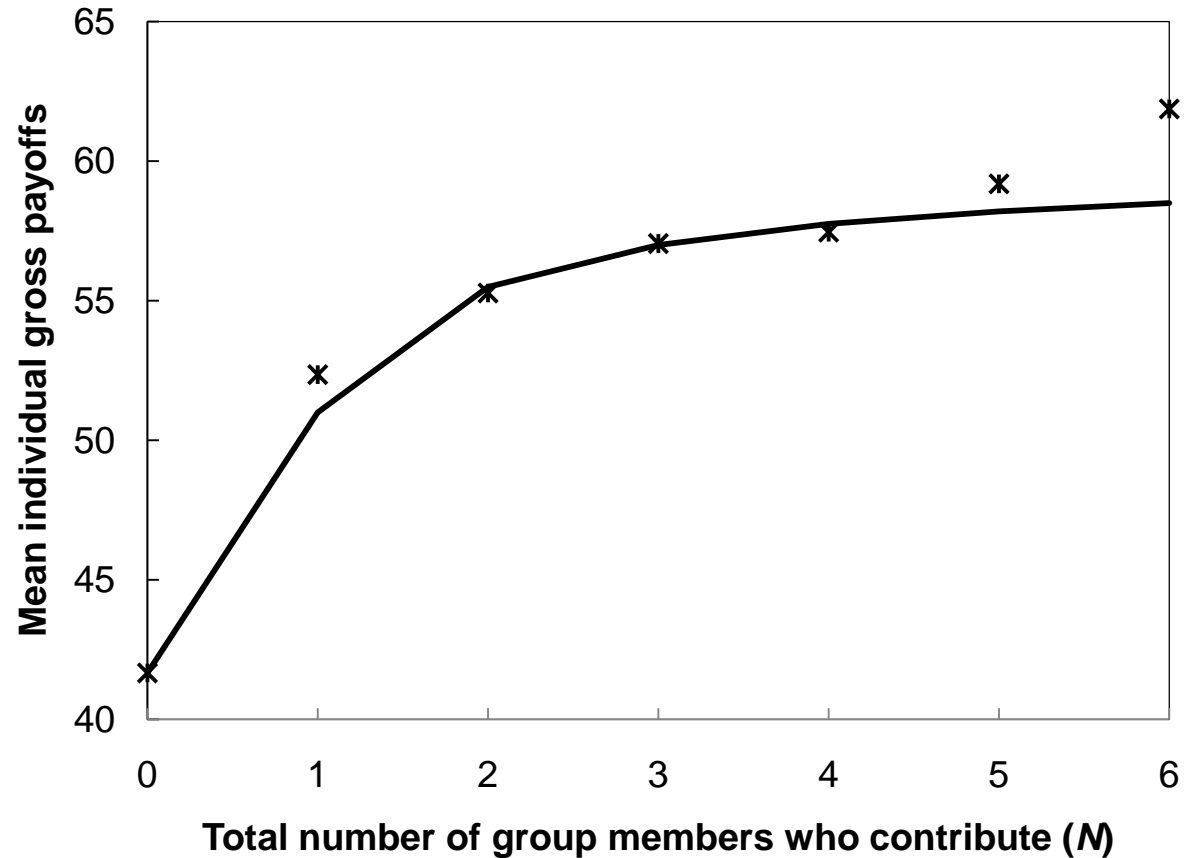
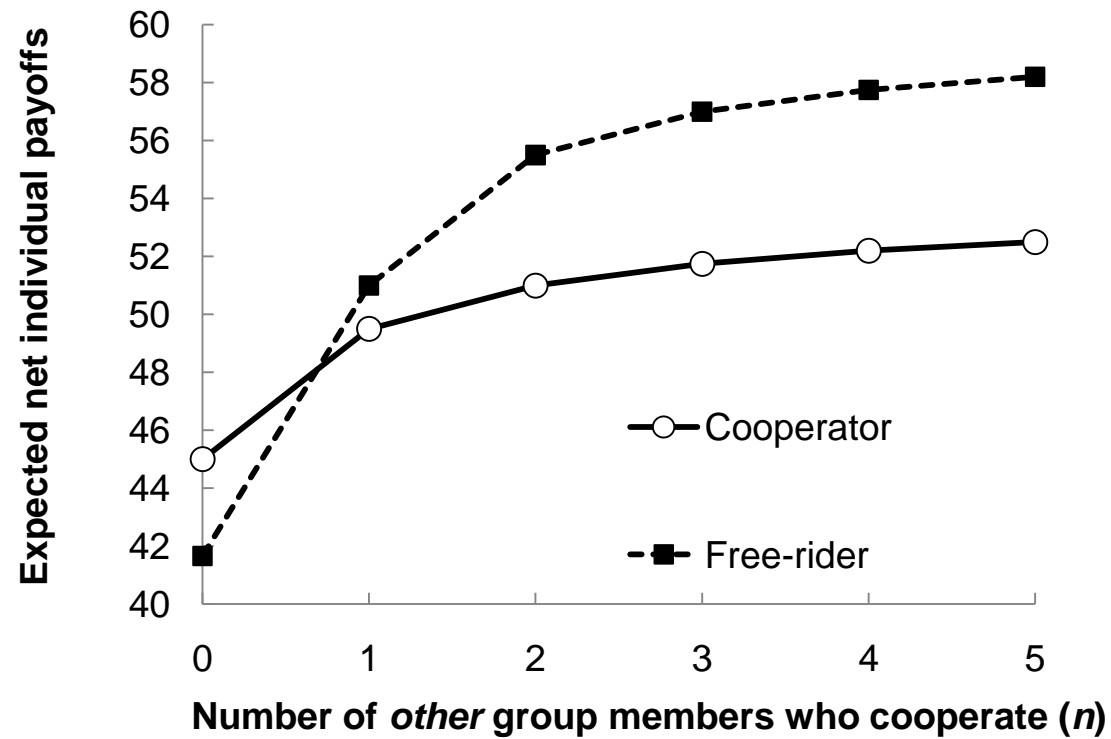


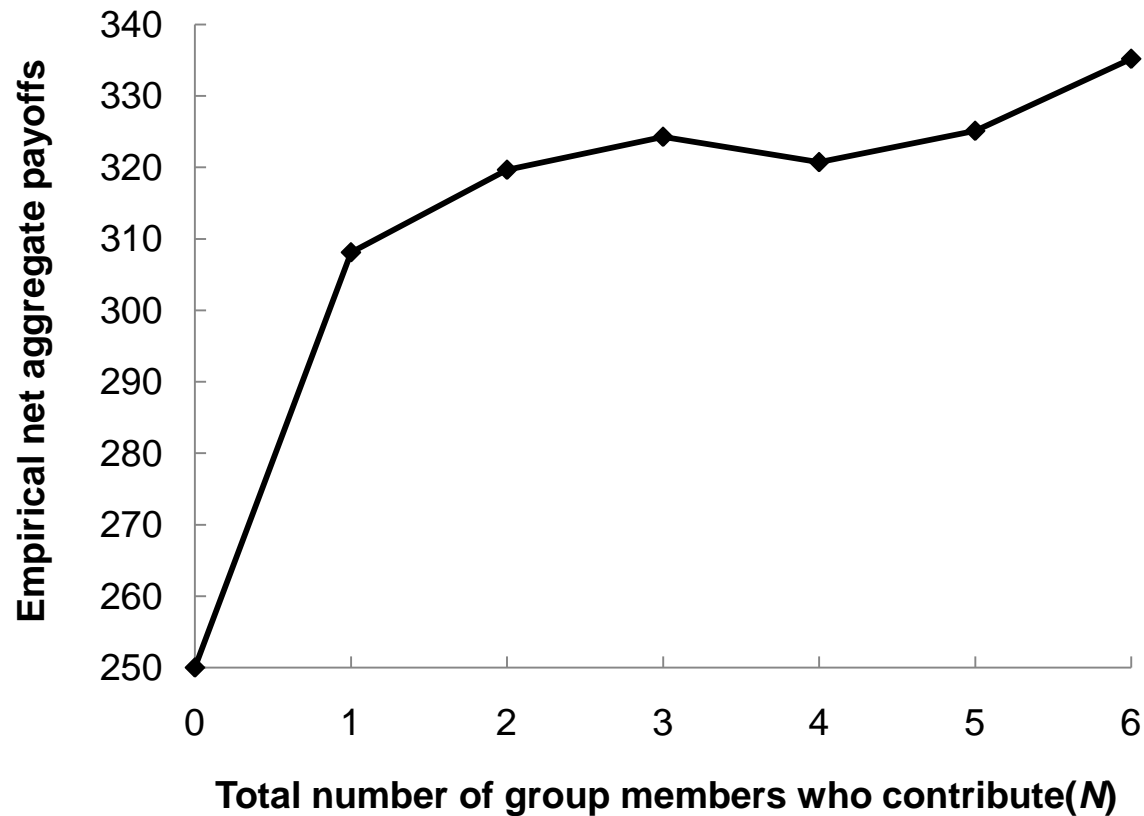
Figure 12. Mean per-trial individual net payoffs (in Yen) in the Majority/Plurality Rule condition and the Best Member Rule condition



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