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The impact of individual versus group rewards on work group performance and cooperation: A computational social science approach

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ABSTRACT

Purpose: To examine the effect of individual versus group evaluation and reward systems on work group behavior and performance under different task conditions.
Methodology: Uses computational social methods using Agent Based Models to simulate work group interactions as different forms of iterated games.
Findings: Group based systems outperform individual based and mixed systems, producing more cooperative behavior, the best performing groups and individuals in most types of interaction games. A new role emerges, the self-sacrificer, who plays a critical role in enabling other group members and the group, to perform better at their own expense.
Research Implications: Suggest opportunities for model development and guidelines for designing real world experiments.
Practical Implications: Helps firms engineer better performing work groups as well as the design of other business systems.
Social Implications: Identifies mechanisms by which cooperation can be developed in social systems.
Originality/Value: Demonstrates the role and value of computational social science methods and agent based models to business research.

1. Introduction

Much of the work of firms is carried out using work groups or teams of interacting individuals, such as in production processes, the development of products and services, service delivery and in managing operations (Cummings, 2004; de Jong, de Ruyter, & Wetzels, 2005; Kozlowski & Ilgen, 2006). As one manager comments: 'We think everything worth doing is done by groups, not by individuals' (Weber, Holmes, & Palermi, 2005, p. 80). Prior research shows that cooperative behavior among work group members plays an important role with more cooperative groups outperforming less cooperative ones (Kozlowski & Bell, 2003).

Useful as such studies are, they tell us little about how and why cooperative behavior emerges and continues in work groups and how managers can engineer greater cooperation. As Kozlowski and Ilgen (2006) conclude, based on an extensive review of the literature, "the dynamics inherent in team processes are still somewhat elusive" (p 97). Developing cooperative behavior in work groups is not easy because of conflicts between individual and group interests. This is especially so when groups comprise individuals with different backgrounds, expertise and interests. Such groups tend not to share information, not to learn from each other or to be flexible in terms of their workloads (Gratton & Erickson, 2007).

More generally, the evolution of cooperation in society, especially among strangers and anonymous opponents is still an unresolved issue (Hammerstein, 2003). Research shows that in general people show high levels of cooperative and pro-social, behavior towards others, even to strangers and anonymous others (e.g. Henrich et al., 2001). This is true of primitive societies and societies with large scale institutions such as market integration and world religions (Henrich et al., 2010; Woodside & Zhang, 2013).

Managers have several ways of potentially improving work group cooperation and performance. One method is to use group or team rewards but "despite hundreds of studies examining team rewards, the conditions under which team rewards will be effective are unclear" (Aimea, Meyer, & Humphrey, 2010, p 60). Prior research focuses on the moderating effect of task interdependence and the rewards for cooperation versus competition (Aimea et al., 2010; Chan, Li, & Pierce, 2014). For example, Wageman (1995) shows that team effectiveness is highest in work groups in which the rewards and tasks have pure individual designs – those in which individual rewards and performance are

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independent of the performance other group members – or pure group designs, where individual rewards and performance of group members are completely interdependent such that the performance and rewards of one member entirely depends on the others' performance. Chan et al. (2014) show that team based rewards enhance performance when worker ability is heterogeneous, which makes cooperation more important in completing tasks. The problem is that group tasks are usually a mix of group and individual interests, a mixture of cooperative and competitive incentives, which leads to the central research question considered here: For what types of group tasks do group or team based rewards outperform individual based rewards?

Computational social science methods can help answer this question. They involve developing agent based computer simulation models that mimic key features of the behavior of work groups and their interactions (Epstein, 2006; Macy & Willer, 2002). The potential value of such methods to studying work group design and performance has been noted before: "Agent-based models have enormous potential to resolve the problem of system-team design … The high potential of this approach means that it merits much broader attention and application in organization team design" Kozlowski and Ilgen (2006, p. 102) and in the examples of the use of such models to study organizations including that by Chang and Harrington (2006) and Prietula, Carley, and Gasser (1998).

Modeling the complex system of interactions among many individuals that characterize work groups is beyond the scope of traditional mathematical and statistical methods (Deissenberg, van der Hoog, & Dawid, 2008; Leombruni & Richiardi, 2005). This is because work groups are highly nonlinear systems in which group behavior and performance emerges through the interactions taking place over time in a bottom up self-organizing manner in a particular context, including the task and the mix of participants' skills, knowledge, attitudes, predispositions and strategies (Kozlowski & Ilgen, 2006). Instead, the study and understanding of the behavior of complex systems like work groups calls for a different approach to science to the traditional experimental and mathematical methods that have served us well for the last 300 years (Jackson, 1996). Axelrod (1997) describes this approach as a third way of doing science.

To build and analyze computational models requires new types of skills, including programming and algorithmic thinking and ways of understanding that challenge traditional ways of thinking and doing research (Jacobson & Wilensky, 2006). Hence they tend to be resisted, currently, in many social science and business disciplines research using these methods is difficult to publish (Harrison, Lin, Carroll, & Carley, 2007). But the situation is changing, with articles explaining and using these methods now appearing in top journals (e.g. Goldenberg, Libai, & Muller, 2001; Lazer & Friedman, 2007; Macy & Willer, 2002; Rand & Rust, 2011; Trusov, Rand, & Joshi, 2013), and special issues of journals have been devoted to the subject, such as the *Journal of Business Research* (Gilbert, Wander, Deffant, & Adjali, 2007), *Journal of Product Innovation and Management* (Garcia & Jager, 2011), *International Journal of Innovation and Technology Management* (Siebers & Wilkinson, 2013) and *Australasian Marketing Journal* (D' Alessandro & Winzar, 2014).

Computational models are a form of mathematical model written in computer code. Just like any model they represent simplifications in order to focus attention on key aspects of behavior. The major advantage of using them is their ability to model and analyze the behavior of complex nonlinear systems, involving many types of interactions and interdependencies. The modeler does not need to make restrictive assumptions in order to make a model mathematically tractable (Tesfatsion & Judd, 2006). The outcomes of computational models are studied using systematic computational experiments, rather than algebraic methods, to determine the logical outcomes of a model under different conditions. Such outcomes can be counterintuitive, because they are complex, nonlinear models (Tesfatsion & Judd, 2006) and because, as Lord May (1976) notes, the education and training of people and researchers is primarily on a diet of linear models.

Examples of the counterintuitive results of even relatively simple nonlinear models include Axelrod's (1984) computer experiments regarding the emergence of cooperation in Iterated Prisoners' Dilemma games, as will be discussed in more detail later. Similarly Schelling's (1971) classic models of urban segregation, in which he showed that even in the absence of any color prejudice, segregated neighborhoods emerge over time in cities.

An alternative to building computational models is to study the behavior and performance emerging in real work groups under different conditions, or to conduct experiments. But the former restricts research to the study work groups under conditions that exist and the researcher can gain access to which does not include all the types of potential conditions that could exist. And the latter requires a very large number of experiments that would be impossible, too costly or unethical to carry out in the real world. But such experiments can be done using computer models (Axelrod, 1997; Gilbert & Troitzsch, 2005; Gilbert et al., 2007; Tesfatsion & Judd, 2006). Furthermore, the outcomes of such computer experiments complement empirical research because they can identify likely conditions producing desired outcomes, which can then be tested in the real world (Held, Wilkinson, Young, & Marks, 2014).

Research already exists which uses computational methods relevant to the study of work group behavior. Axelrod (1984, 1987, 1997) and Axelrod and Hamilton (1981) undertook important pioneering work using computational methods to study the evolution of cooperation and performance among interacting individuals. They did this using Iterated Prisoner Dilemma (IPD) games to model interactions involving a mix of competitive and cooperative motives. Their computer experiments provide the basis for the research described here, which models work group interactions as forms of interaction games. The research described here builds on and extends the work of Axelrod and his colleagues in many ways, including using examples of all types of games, not just the IPD and to examine the impact of group as well as individual evaluation and reward systems on the emergence of cooperation.

The findings show that group based evaluation and reward systems outperform individual based or mixed reward systems for a large number of group situations. Individual based systems outperform group and mixed systems only when individual and group interests are aligned, that is when the action that benefits an individual also benefits the group. The findings are consistent with empirical research that shows that the group task is an important moderator of the effect of group cohesion and shared knowledge and cognitions on group effectiveness (Kozlowski & Ilgen, 2006). These conditions aid coordination and the cooperation processes within groups when the group task is more complex and greater interdependencies exist. In such situations more opportunities for conflicts of interest arise such that group and individual performance are not aligned.

The findings also reveal the conditions under which no significant difference between the outcomes of group and individual evaluation and reward systems exist. This will help managers to identify and focus attention on work group situations where the design of the reward system matters.

Another finding is that, counter-intuitively, group incentives produce the highest performing individual strategies in many types of games because they produce and sustain better mixes or ecologies of strategies. As in biology, the success of a given type of animal's behavior strategy does not depend only on itself but also on the behavior of other animals and their interactions with them, as well as on the environment in which they operate.

Lastly, the findings suggest the existence of a new type of role in work groups, the self-sacrificer. These individuals induce superior performance in others in the group and the group as a whole at the expense of their own performance. They resemble but are quite different from free-riders, who simply exploit the group for their own benefit. Individualist evaluation and reward systems do not reward and retain self-sacrificers in groups. Instead, they are poorly evaluated and removed from the group or they are induced to change their behavior in ways that are likely to harm group performance.

These research results have important implications for researchers and managers in designing and implementing evaluation and reward systems. For example, for researchers they point to key types of real world experiments that need to be conducted to test the effects of evaluation and reward schemes on group behavior and performance. This includes the need to allow for group interaction effects which is not the norm - see for example research on sales teams by Lim, Ahearne, and Ham (2009). The results can also help guide managers in designing reward systems for different types of work group conditions.

The next section reviews research concerning the evolution of cooperation, introduces theories of group selection and relates them to cooperation in, and the performance of, work groups. The following sections describe the model of work group interactions and performance, the analytical methods and the findings. The concluding section discusses the research and management implications of the results.

2. The evolution of cooperation and performance

As already noted, Axelrod and Hamilton conducted pioneering research studying the evolution of cooperation and performance among individuals using two-person Iterated Prisoner's Dilemma (IPD) games (Axelrod 1984, 1987, 1997; Axelrod and Hamilton (1981)). The Prisoners' Dilemma (PD) is a game in which two players have to decide whether to cooperate (C) or defect (D) (not cooperate) with each other, with the performance or payoff for each player dependent on both their own and their partner's choices. The game is used extensively to study individual interactions in many situations because the game has incentives to both cooperate and compete - see for example Kendall, Yao & Chong, 2007; McNamara, Barta, & Houston, 2004 and Stephens, McLinn, & Stevens, 2002. If both players cooperate they do equally well, but if one cooperates and the other defects the defector gets a greater payoff and the defector gets the worst possible payoff of the game. If they both defect they each do badly but better than if they cooperated and the other defected. In a one-time interaction the best strategy is to defect, not cooperate, to avoid the worst possible payoff. In an iterated game, these payoffs accumulate over successive interactions making the best strategy unclear. Axelrod and his colleagues showed that a simple cooperative strategy, Tit for Tat, or some variant of the strategy, resulted in the best overall performance. This strategy begins by cooperating and then does what the other player does in the previous interaction.

In a work group context group members interact with each other and the results or payoffs may be interpreted as the performance of an individual in such interactions, such as the number of units produced or the number of tasks completed per period. Individual performance depends on the actions of others in the group.

An example of an Iterated Prisoners' Dilemma (PD) type work group situation is when a team faces pooled task interdependence (Thompson, 1967; Van de Ven, Delbecq, & Koenig, 1976). This is where workers have common tasks and inputs, like sharing the use of equipment and/or space that has to be maintained and cleaned up each period. To illustrate how this can be modeled as a PD game, suppose that if both workers cooperate in a period (CC) 5 units of output are produced by each. But if one decides to not cooperate (defect), such as by shirking on the common tasks, and exploits the cooperative behavior of another (DC or CD), who does all the common tasks, the defector's output increases at the expense of the cooperator. Say the defector's output increases to seven units and the cooperator now produces only two units, this means that total output is reduced to 7 units ($5 + 2$). In other words the defector's gain outweighs the cooperators loss of output. If both workers refuse to cooperate (DD) they each produce less, say 3 units each, because common tasks are not done by anyone or done very poorly. This is not as bad for an individual compared to the case where they cooperate and the other defects but this behavior results in the lowest possible total output.

This situation resembles the relationship between shifts in a soup factory described by Katzenbach and Khan (2010). In that case individual shifts shirked (defected) on tasks such as cleaning and preparing the work space for the next shift, which improved the first shifts output at the expense of the next. Overall performance suffered due to this behavior and was only improved when new performance metrics and communication and feedback systems were introduced that rewarded total performance, rather the output of individual shifts. The result was due to the emergence of more cooperative behavior and improved morale.

The research conducted by Axelrod and his colleagues focused on the behavior and performance of individuals rather than groups and on one type of interaction situation the IPD. Subsequent research also follows this pattern, with group level effects largely overlooked except for a few exceptions. Axelrod (1987) considered these effects in terms of spatial models, whilst Bowles, Choi, and Hopfensitz (2004) show how the existence of certain types of group level structures may encourage the evolution of group beneficial traits. Similarly, Matros (2012) found that altruism may survive in groups, although this is dependent on the decision rules of those involved. Empirical work aimed at improving group performance also focuses mainly on the individual, without taking into account the group context, the team as a collective actor, or the roles and contributions of individuals to team processes and performances (Kozlowski & Ilgen, 2006).

The potential relevance and importance of group level effects is reflected in evolutionary theories of group selection, which have been applied to social systems (Henrich, 2004; Wilson & Gowdy, 2013). Group selection theories recognize that animals and people do not interact randomly with each other but form groups or ecologies involving interactions among different types of actors (animals and plants) that affect individual and group performance and survival. Work groups are an example of this.

A dramatic illustration of the power of group selection is provided by an experiment seeking to improve egg production. In this case the work groups are battery hens whose reproduction is managed by farmers. Selective breeding of the hens raised in cages that lay the most eggs is the way farmers usually operate, which results in birds that lay more eggs but who are very aggressive to each other, have reduced life spans and produce lower quality eggs. But an experiment by Muir (1996) showed that selective breeding of the best performing cages or groups of hens, rather than individuals, results in even more eggs of a better quality and hens with normal life spans who get on well with each other. He has since shown that similar results occur in other types of animal and plant communities (Muir, 2005). His results have led others to reexamine theories of cooperation in animal and social systems, for example see research by Henrich, 2004 and Wilson & Sober, 1994).

Parallels exist with the design and management of work groups. Most evaluation and reward systems in organizations follow the logic of individual selection; they focus on the performance of the individual and not the group (Ilgen & Sheppard, 2001). This encourages individuals to behave in ways that increase their own performance at the expense of the group's, to the extent these two conflict (Kozlowski & Ilgen, 2006). Theories of group selection point to the potential importance of group level evaluation and reward systems, which can encourage more cooperative behavior and potentially better work group performance (Arya, Fellingham, & Glover, 1997; Che & Yoo, 2001; FitzRoy & Kraft, 1987).

But the link is not straight forward. Research shows that group incentive mechanisms may produce enhanced performance but this depends on group conditions (FitzRoy & Kraft, 1995) and the design of the incentive scheme. For example, Nalbantian and Schotter (1997) show that relative performance schemes outperform target based schemes. Also playing a role are: the interactions between group members (Encinosa, Gaynor, & Rebitzer, 2007; Libby & Thorne, 2009); the types of incentives (Lavy, 2002); previous reward systems (Johnson et al., 2006); job image (Akerlof & Kranton, 2005); types of group members (Goette, Huffman, & Meier, 2006); society and company norms (Fehr & Fischbacher, 2002); individual personalities (Beersma et al., 2003; Ellis et al., 2003); and the ability of individuals to hold up output (Kvaløy & Olsen, 2012).

The risk of free riding and the inability to detect this behavior is often cited as the main argument against group based incentives (see for example Hamilton, Nickerson, & Owan, 2003). One possible solution is the use of mixed incentive schemes, rewarding both individual and group performance. Libby and Thorne (2009), however, show that they may not be beneficial as they can confuse employees.

The complexity of the relationship between the problem setting and performance makes drawing conclusions regarding the applicability of group incentive systems difficult. A number of factors are in play over time, probable lags between incentives and performance and long term performance matters. As noted already, empirical studies cannot consider all the factors involved because of limits to the empirical evidence available and the time and costs involved of doing all the experiments required. A way forward is to use computational social science methods, the methodology used here. More specifically, the research described here builds on and extends the classic research by Axelrod and his colleagues to examine the conditions under which group based incentive systems do and do not outperform individual based incentive systems and mixed systems. The analysis considers the results for a sample of all possible types of games, not just IPD, in order to reflect a greater variety of potential interaction situations and payoff structures that may be encountered in work groups. No previous research has been found that systematically compares the impact of group versus individual reward systems for all types of game conditions.

3. A computational model of work group interactions

This section describes an agent based computer simulation model in which the agents are individuals with strategies for interacting with others in groups under different work group situations. The agent based model simulates interactions between pairs of individuals as different types of iterated games. The model uses two types of evaluation and reward systems to form and change groups over time: 1) Group Selection, which rewards the best performing groups by selecting and retaining them; 2) Individual Selection, which rewards the best performing individuals in groups by selecting and retaining them. The model uses a genetic algorithm, a computational technique that mimics natural selection, to represent the two types of evaluation and reward systems, as explained below. In real groups individuals do not go through the type of evolutionary process used in the simulations; instead this is a mechanism to determine equilibrium behavior in different circumstances (Riechmann, 2001). As such, this model is normative, rather than descriptive of the mechanism by which group selection occurs.

3.1. Selection and reward systems

Individuals interact within groups and the interactions take the form of two-player, iterated, binary choice games in which players either cooperate or defect (which means they do not cooperate). Individual performance depends on what both players do and the specific form of the interaction game played. Four possible types of interaction can occur. Both players can cooperate and achieve the CC performance outcome; if Player 1 defects whilst Player 2 cooperates Player 1 achieves the DC performance outcome; if Player 1 cooperates whilst Player 2 defects Player 1 achieves the CD performance outcome and if both players defect they each achieve the DD performance outcome. Note these games are symmetric, so if Player 1 achieves the CD performance outcome by cooperating whilst Player 2 defects, then Player 2 achieves the DC performance outcome. The CC, CD, DC, DD notation used through the remainder of this paper indicates the way players perform in a given interaction.

The population consists of n players divided into m groups, each of equal size (n/m). In each generation every individual plays a specific two-player game with every other individual within the group in turn. Each interaction lasts for r rounds. The iterated games allow players to condition their behavior on that of their partners and their previous interactions with those partners. In this way they can try to punish or reward others based on the way they behave. Arya et al. (1997) and Che and Yoo (2001) both show that the ability to monitor and punish opponents is potentially important in successfully employing group reward schemes.

All members of the group interact equally frequently with all other members in this model. However, this is not a necessary part of the model. A network structure could be imposed on each group, which would determine the frequency and nature of individual interactions. The network could be determined endogenously (e.g. Fosco & Mengel, 2011) or players could select and refuse partners based on their previous behavior, like the models of Ashlock, Smucker, Stanley, and Tesfatsion (1996). Previous research shows that the structure of relations within a group or units within an organization can influence its performance, see for example Cummings and Cross (2003) and Ethiraj and Levinthal (2004). Here the model uses a simple stylized form of group structure in order to separate and demonstrate the effect of the reward and evaluation mechanism. The effect of more complex group structures is an open question for further research.

Groups in this model represent teams of individuals interacting in a company or similar setting. By modelling groups as a collection of individuals playing two-player games the model allows for a wide range of strategic possibilities. Players may potentially exploit or assist other individuals within the team to maximize their own or group performance. Their behavior depends on their own strategy and the strategy of each individual with whom they interact. For example, one player's strategy may mean they try to exploit some members of the group for personal gain but at the same time cooperate with others who show a propensity to retaliate. An alternative would be to consider n-player games, where more than two players interact at the same time. This, however, constrains the scope of strategies and interactions because, in an n-player game, players cannot respond in different ways to different players, they can only act based on the sum of every player's actions in the previous period. This may be an interesting future extension of the research.

Each individual's strategy dictates how they play the game. A strategy specifies the player's responses to all possible game situations. The set of situations a player may face is dependent on their memory length. With two possible actions (cooperate and defect), and a memory length of k, 2^k possible game situations can occur that the player must respond to; that is the number of possible types of two period histories of behavior. For example, Tit-for-Tat only responds to the behavior of the other player in the previous period, which means the Tit-for-Tat player remembers the behavior of the other player in the previous period and responds accordingly. In this case the strategy has only two possible histories to respond to - either the other player cooperated or defected in the previous period. If a player has a memory length of two, the player responds to the previous two periods of the other's behavior. This means the strategy has four possible histories of the other's actions to contend with, which are: (D,D) where the other player defected in the last two periods, they defected then cooperated (D,C), cooperated and then defected (C,D) or cooperated both times (C,C). Note that, by convention, behavior separated by commas in brackets describe past behavior.

With a two period memory, a strategy must describe a player's responses in the current period to all four possible two period histories. An example is DCCC. In the notation used in the model the D in position one of the strategy indicates what the player does if the other defects in the previous two periods (D, D). The C's in positions two, three and four indicate that the player will cooperate in the current period in all other possible two period histories which are in order (C,D) (D,C) or (C,C)).

The strategy is not complete because the player's behavior at the game's beginning is not specified. At that point the strategy has no two period history to respond to because they have not yet interacted. To resolve this, a player's strategy includes a fictitious "memory" that indicates how the player will behave in the first interactions, its opening stance. A two period memory requires specifying a players behavior in the first two periods of interaction. By convention, the string describing a strategy starts with these responses. Hence, a strategy string of CC|DCCC comprises a fictitious two period history of (C,C) in the first two positions followed by the rules of behavior for each of the four possible two period histories (DCCC), as described above. These rules of behavior also specify how the player responds to its fictitious initial two period "memory". The fictitious history memory is a kind of initial orientation or attitude, the degree of cooperativeness or competitiveness a player brings to the game at the outset. For example, a player with a fictitious memory of (C,C) and the rules of behavior DCCC cooperates in the initial period. In the next period, the player has a one period real memory of what the other player did in the initial period and replaces the fictitious memory. The initial fictitious memory of behavior in the previous period now moves to become the fictitious memory of two periods ago. For example, if the other player defected in the first period, in the following period the two period memory changes from (C,C) to (C,D). The remainder of the strategy string, DCCC, indicates the player will still cooperate in the following period. After period three is the strategy has a real two period history and the fictitious memory no longer affects the player's behavior. From then on a player's behavior depends only on its actual two period memory of what the other player did, which a player updates after each period. With a three period memory, a strategy has eight possible three period histories to contend with, plus an initial fictitious memory of three periods, for example (DCC|DCDCCDCC). More generally, with a memory length of k, a strategy has 2^k possible k period histories to contend and the strategy must specify responses to each of them plus k periods of fictitious memory.

A genetic algorithm (Holland, 1975) models the evaluation and reward systems, which optimize strategies in a similar manner to Axelrod (1987) and Midgley, Marks, and Cooper (1997). At the start of the simulation, individual strategies in groups are randomly generated. Time proceeds in generations. In each generation each individual plays all other individuals in their group a fixed number of times or iterations. An individual's total performance is the sum of its performance from all the iterated games played against all other members of the individual's group. The group's overall performance is the sum of the performances of all players within a group. After calculating performance the algorithm determines the next generation of players from the existing population. Individual selection focuses on the high performing individuals, whilst group selection focuses on the high performing groups. Retention is both direct, by keeping high performing individuals and groups and their strategies in the next generation and indirect, by creating new individuals and groups from existing high performing behavior strategies. Direct retention guarantees the best performing strategies survive whilst the indirect method allows improvement. Under individual selection the best performing individuals are the n/2 individuals in the population with the highest performance. The genetic algorithm (GA) inserts these individuals into random groups in the next generation (direct retention). The algorithm also forms new strategies by randomly choosing pairs of the best performing individuals and creating a new strategy (indirect selection) by combining the first part of one strategy with the second part of the other (a technique known as "crossover"). The GA chooses the break or crossover point randomly from a uniform distribution. To illustrate the procedure, suppose the first individual selected has the two period memory strategy of CD|DCDD, the second has DC|DDCC and the randomly chosen crossover position is 4. The newly created strategy is CD|DCCC, which combines the first 4 elements of the first individual's strategy and the last 2 elements of the second. In biology crossover mimics reproduction, whilst in social systems crossover can be thought of as a form of learning and sharing of strategies within a population. After crossover, a small probability (5%) exists for a single point mutation in a strategy in which a D flips to C or vice versa, which, in social systems, may be thought of as errors in copying another's style of behavior. Next the GA randomly allocates the n/2 new individuals to groups.

Under group selection the GA selects the m/2 best performing groups and inserts them into the next generation (direct retention). The GA forms the remaining groups by combining pairs of individuals selected from the best performing groups at random, irrespective of their individual performance (indirect retention). As with individual selection, a single point mutation occurs with a 5% probability.

The GA identifies an equilibrium, that is a population of strategies maximizing performance for the given selection mechanism. The GA repeats the process for 1000 generations. Convergence, defined as group and individual performance being on average constant, occurs relatively early, typically after 100 generations. Games are played for $r = 200$ rounds. Examining different numbers of rounds reveals no effect on the results. The population size is $n = 64$, whilst the number of groups is $m = 8$. The memory length is $k = 3$. Simulations with different population sizes and memory lengths are not qualitatively different and are available from the authors on request. Different group sizes have a small effect on the results, primarily for groups of size two. The two group case does not have many of the interaction effects, as each player only ever plays one other. As a consequence the population behaves like one large group. For larger group sizes the results are qualitatively similar.

In any computational experiment verification and validation of the algorithm are important to ensure accuracy and reliability of results. In this case both the game set up and the GA are standard computational tools, which simplifies the analysis. All of the components of the model, were tested individually. A test of the mechanism by which individuals play compared the computed results to those calculated by hand for a sample of games and strategies to ensure the two were identical. The GA was tested in stages. Sample populations were subjected to the group and individual based selection mechanisms and the resulting populations analyzed to ensure that the observed behavior matched that specified above. The occurrence of mutations and crossovers were observed and compared to the parameters specifying their frequency to verify they matched. Further, none of the parameters controlling the GA - the probability of mutations (errors), the probability of crossovers and the number of crossovers qualitatively affected the results showing that the exact specification of the genetic algorithm is not responsible for the findings. The code for the simulations is available in the journal repository.

4. Results

To determine the conditions in which individual or group selection is superior, a broad range of games were considered. Rapoport and Guyer (1966) identify 726 strategically distinct 2 by 2 games in which individuals have different rankings of performances, reflecting different types of interaction situations. In this model the absolute values of the performances matter, the actual amount of payoff, rather than simply their ordering, in determining strategy success. This is because an individual's performance is the sum of the performances over the repeated interactions of the game against all group members. Consequently, an infinite number of possible games exist, making an exhaustive analysis impossible. In order to bound the analysis a sample is drawn from the space of all possible games and integer multiples of 0.1 in the range [0,1] define performance outcomes. An example of a game is where the payoffs for each player are $CC = 0.5$, $DC = 0.7$, $CD = 0.1$, $DD = 0.2$. This means that when both players cooperate their performance is each 0.5 and is the maximum possible combined performance of 1 in this game. When a player defects and the other cooperates the defector's performance is 0.7 and the cooperator's is 0.1 for a combined 0.8.

When both defect the performance of both players is 0.2 and the combined total is 0.4. The resulting number of games in the simulations is 14,641 including all possible rank orderings of performance. This means that the figures summarizing the results in the following sections are necessarily dense because they derive from so many thousands of individual simulation runs. Some games cannot be represented in this format, for instance games that would produce lexicographic preferences - those in which the payoff for a single instance of a particular outcome exceed the sum of outcomes for any other action across all rounds of the game. Nevertheless, this set is substantial and sufficient for the analysis both in terms of its breadth and detail.

4.1. Group versus individual selection and reward

Figs. 1 and 2 show the selection and reward mechanisms producing the best group and individual performance for the range of games described above. A white cell corresponds to games where no differences exist between group and individual evaluation and reward mechanisms, black cells to those where group selection produces higher performance and grey cells when individual selection produces higher performance. The results of each simulation of a game vary depending on the random seed used, which affects the starting conditions, the outcomes of the genetic algorithm and mutations. For this reason simulations were repeated 1000 times for group selection and individual selection for each game, leading to a sample of results in each case. The analysis of results focused on mean differences significant at the 99% level. These results are presented in Fig. 1. In all panels the performances for different values of CD and DC, which are the rewards given to players cooperating when the other defects and those given to defectors when the other cooperates, vary along the x and y axis respectively. Each panel represents different values of DD performance as indicated and all the panels have the CC performance set at 0.5. Analysis of the results for different values of CC are qualitatively similar and available on request.

Differences exist between the outcomes of individual and group selection mechanisms. Fig. 1 shows distinct areas within which one of the two selection mechanisms produces significantly better performing groups. Areas also exist where the results show no significant differences between the two mechanisms. The black area in which group selection performs better, is much larger than the grey areas where individual selection performs best.

Whilst the black area appears to be contiguous, the area comprises several distinct sub-regions, reflecting different types of games. The first is the area bounded by DD ≤ 0.5 and CD + DC > 1.0, the triangle in the upper right that is most clearly identifiable in the sub figure for DD = 0.5. In these games the highest combined performance is from anti-coordination, in other words playing C when your partner plays D or vice versa. Consider for example the game in which the performances are CC = 0.5, DC = 0.8, CD = 0.4, DD = 0.0. The best combined performance in this case is if one individual cooperates and the other defects because the combination of DC and CD produce 1.2 units of performance whereas the CC/CC and DD/DD combinations produce 1.0 and 0.0 respectively. The defector's individual performance is much better than the cooperator's. Under individual selection this will lead to an increase in the number of defectors and therefore more DD interactions within the population, which reduces group performance. In this game situation group selection selects the optimal mix of cooperators and defectors to ensure more CD/DC interactions that maximize performance. This type of game resembles simple or modular coordination tasks or sequential task dependence (Thompson, 1967) in which individuals specialize in different sub-tasks that can be assembled or added together, as when groups of workers take turns in digging a hole, recording results, or serving different customers in a market (see for example the experiments of Selten & Warglien, 2007 and Weber & Camerer, 2003).

The second segment is approximately bounded by DD ≤ 0.4, DC ≥ 0.5 and CD + DC < 1.0. This corresponds to the area of games in the upper left of the first five sub-figures and is contiguous with the region previously described. In this area, mutual cooperation produces the highest combined performance but defection against a cooperator produces a

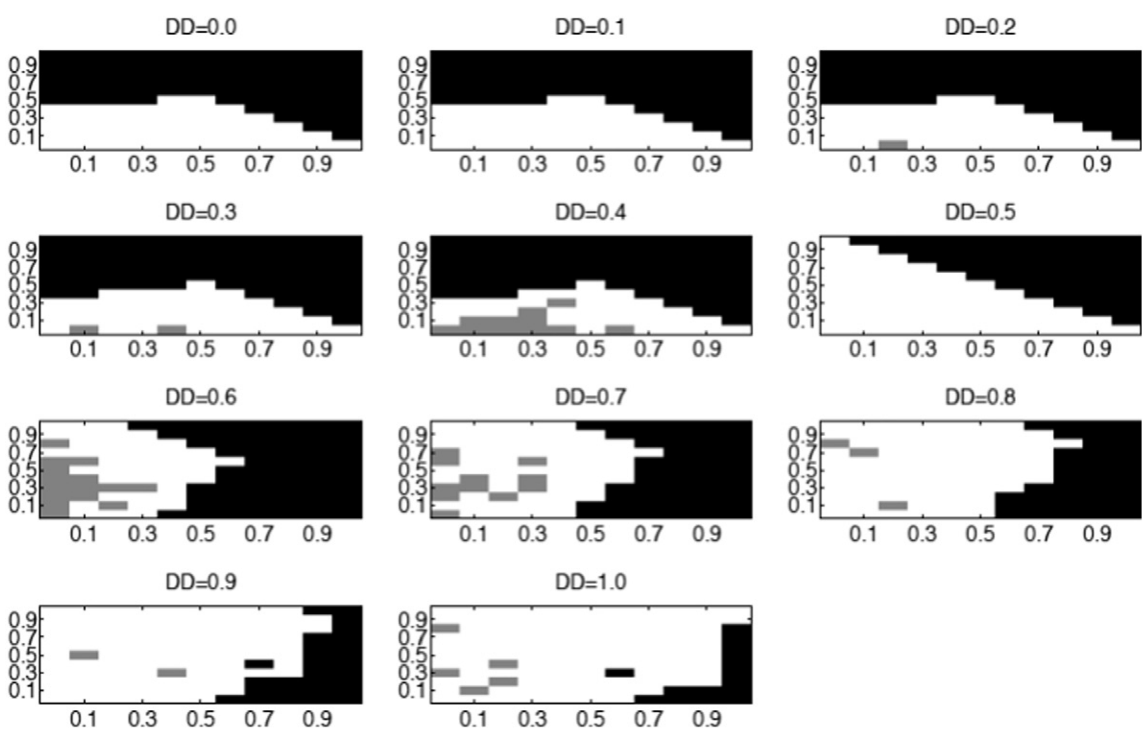

Fig. 1. Best performing groups: comparison of group and individual selection and reward mechanisms.*. *Simulations results for best group performance in the final generation for different interaction games. In all cases CC = 0.5, different values of CD on the x-axis, DC on the y-axis and DD across panels. 1000 repetitions conducted for each game, and selection and reward mechanism. White squares correspond to no significant difference in scores. Black squares are games in which group selection produces superior results and grey squares are those in which individual selection is superior. In all cases differences are significant at the 99% level.

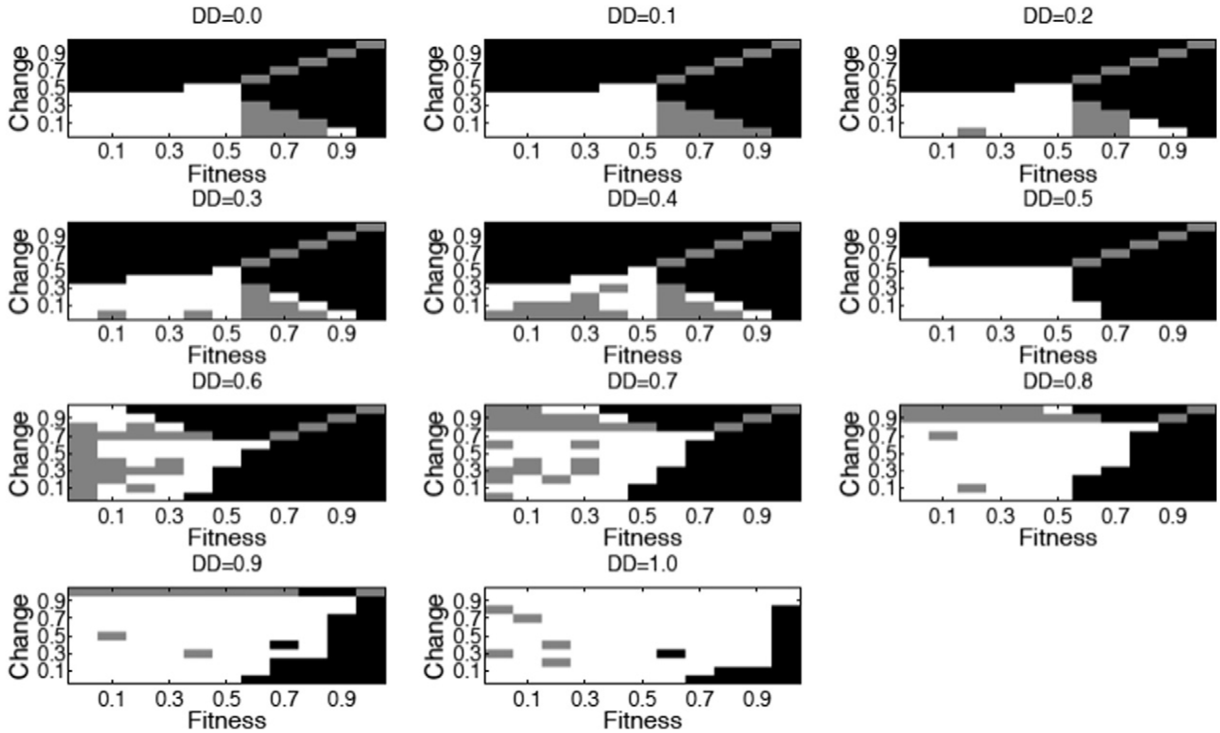

Fig. 2. Highest performing individual performance: comparison of group and individual selection and reward mechanisms.*. * Simulations results for best individual performance in the final generation for different interaction games. In all cases CC = 0.5, different values of CD on the x-axis, DC on the y-axis and DD across panels. 1000 repetitions conducted for each game and selection mechanism. White squares correspond to no significant difference in performance. Black squares are games in which group selection produces superior results and grey squares are those in which individual selection is superior. In all cases differences are significant at the 99% level.

higher individual performance. The Prisoner's Dilemma game exists in this segment. Like the area discussed above, individual selection rewards those players who defect as they increase their individual score at the expense of the group's performance. Group selection allows the population to settle on an equilibrium that is beneficial to all. The performance favors those who mutually cooperate and group selection encourages the existence of these strategies. The final area in which group selection is superior is the triangle bounded by DD > 0.5, DC < 0.5, CD > 0.5 (the bottom right in those figures for DD > 0.5), where the combined performance for DD is the same or more than CD/DC and more than CC. This is equivalent to the first region except that the performance matrix is mirrored, with DD being the equivalent of CC. Hence the explanation is similar. The best performing groups contain the most defectors but if CD is less than DC and CD is greater than CC, individual selection will favor the cooperator, which moves the groups away from mutual defection.

Individual selection does better for a range of games in the bottom left of the sub-figures. In order to maximize group performance all players must synchronize on either CC or DD, depending on which is higher. The CD and DC scores are such that if an individual changes strategy when in the lower performing equilibrium, they reduce their own performance but this reduces the group's performance by even more. For example, for the game in which CC = 0.5, CD = 0.3, DC = 0.0 and DD = 0.4 a single co-operator in a group of defectors receives 0.3 every time they play and their opponent's performance is 0.0. For CC = 0.5, when DD is between 0.4 and 0.7, the pure CC and DD performances are sufficiently similar that the optimization method may initially identify either. The actual choice will depend on the random distribution of strategies at the start of the model. Under group selection, the sub-optimal strategy is very hard to change if a population synchronizes on such a strategy. A single player changing will reduce the group performance, even though the individual's performance is increased, leading to the group not being selected. Under individual selection the change in strategy increases the individual's performance, leading to their selection and their behavior spreading in the population and, in time, the whole population adopts the superior strategy. Note that for DD = 0.5 both DD and CC are equally good and so switching is not necessary. In other words group and individual performance incentives are aligned such that what is good for group performance is equally good for the individual and vice versa.

The overall pattern of results is that group selection does better than individual selection when individual and group performance incentives are not aligned. To achieve the optimal performance some individuals must sacrifice their own performance for the good of the group as a whole. A Pareto optimum occurs when those who sacrifice their own performance for the greater returns to the group as a whole can be compensated. These self-sacrificers, hence play an important role in groups in these situations but are quickly eliminated from the population under individual selection. This is a novel finding as the role and importance of such self-sacrificers and the way they affect group performance has not been identified and discussed before. This finding raises issues as to how and when managers can identify and nurture such behavior and the conditions in which they are valuable.

A large range of games exist for which the two mechanisms do equally well. In these areas both individual and group selection are able to find strategies that are equally effective. This means that, in work groups conforming to these patterns of behavior interdependencies, the types of incentive and reward systems used do not matter, which helps focus the attention of managers on the types of groups in which they do matter.

Fig. 2 shows that group selection produces the best performing individual in nearly half of all games. This is surprising because the individual based selection mechanism is designed to maximize this quantity. The ranges in which this is true closely match those in which group selection also produces the best performing groups. The conditions that lead to high group performance also produce the best individual performance. This is because, under group selection, the mix of strategies in the group that produces the best individual performance survives, whereas under individual selection the high performing individual strategies will spread among groups and reduce overall performance as they compete more against each other.

Not only does group selection produce the best performing individuals overall, group selection also produces in many cases the worst overall performing individuals. This is not shown in the figure. These are the aforementioned self-sacrificers in groups, whose poor performance helps increase group performance. These worst poor performers are essential to the superior functioning of the group because they enable others in the group to perform much better as well as the group as a whole. Individual selection eliminates such individuals, whereas group selection does not.

The worst performing individuals are not always self-sacrificers - those individuals which boost the performance of the group at their own expense. Self-sacrificers can only exist when superior group performance requires a particular mix of cooperation and defection and, when self-sacrificers interact with each other they do not perform so poorly as to offset the increase in the performance of others in the group. When all individuals have to cooperate (or defect in some games) to produce superior group performance this results in no differences in the performance of each individual and hence no self-sacrificers. For example, the PD game described earlier, where CC = 0.5, CD = 0.1, DC = 0.7 and DD = 0.2, produces the best performing individuals under group selection and group members score 0.5 each time from cooperating. Individual selection produces the worst performing individuals who score 0.2 per round.

Self-sacrificers emerge when group selection produces an equal mix of co-operators and defectors. In general, for large groups this will be the case if: CD + CC + DC + DD > 4 max(CC,DD). In this case the payoffs from the mixed strategy (cooperating with defectors) compensate for the times when players end up cooperating with cooperators and defecting with defectors. For example, in the PD game where CD = 0.1, CC = 0.5, DC = 0.7 and DD = 0.2 the sum of all the payoffs is 0.1 + 0.5 + 0.7 + 0.2 = 1.5, which is not greater than 4 times the maximum of 0.2 and 0.5. So, in this case group selection produces pure CC strategies.

If the game instead is: CC = 0.5, CD = 0.4, DC = 1.0 and DD = 0.2, the sum of all payoffs 0.4 + 0.5 + 1.0 + 0.2 = 2.1 and is greater than 4 times the maximum of 0.2 and 0.5. In this case group selections produces a mixed strategy that includes self-sacrificers, who cooperate, which assists defectors in producing 1.0 each interaction with them, whilst they produce 0.5.

Now consider individual selection. This produces the best performing individual in the set of games for which CD = DC and CD > 0.5 and DC > 0.5. Here, the CD/DC option results in the greatest individual performance. Within this region individual performances are maximized by being in the minority in the group. The regular mixing of individuals occasionally allocates a defector to a group of cooperators, or a cooperator to a group of defectors in some games. This results in high individual performance but a low group performance (Fig. 1). Off this diagonal an advantage exists for either one action or the other. In these regions the ability to maintain a better group composition provided by group selection outweighs the selection benefits of individual selection, leading to higher individual performance. A second area in which individual selection does better is the small light gray triangle in the region DD ≤ 0.4, CD + DC < 1.0 and CD > 0.5. In this region individual selection does particularly well because of the noise introduced by the selection process. Occasionally, mutations lead to individuals who defect. Defection in these games damages the defectors' performance but gives small increases to others in the group. As a result, the presence of one of these individuals leads to the group containing the best performing individual in the population. At the same time the group's overall score is reduced, meaning that they are not the highest performing group. Other instances exist where individual selection produces the best performing individual overall, although the areas in which this occurs are somewhat diffuse. The reason for this is that when a particular combination of strategies results in a higher performing individual, this individual's behavior spreads throughout the group and their performance is reduced. Consequently, the performance of the best individual is partially dependent on timing and the games that they are in appear to have little pattern.

4.2. Strategies emerging

In order to better understand the behavior of players under the two selection and reward mechanisms, consider the player strategies in a sample game. Table 1 shows the set of strategies present in the 1000th generation for a version of the Prisoners Dilemma with performances CC = 0.5, CD = 0.1, DC = 0.7 and DD = 0.2. Each cell of Table 1 gives the fraction of individuals who cooperate in that location of their strategy. The first three columns are the three period fictitious history, labeled $H_{t\text{-}3}$, $H_{t\text{-}2}$ and $H_{t\text{-}1}$, whilst the next eight columns indicate whether the strategy cooperates of defects to each possible three period history. A Z-test and a significance at the 99% level was used to test for difference in the proportions cooperating between the two selection mechanisms. An asterix indicates significant differences.

Table 1 shows no dominant strategy, unlike the results found by Axelrod and Hamilton (1981), instead a mix of strategies result in high performance. A single dominant strategy exists if all entries in the table, are either 0% or 100%. A mix of strategies emerges because different strategies can produce the same pattern of behavior. For instance, against a player who always cooperates, a strategy that defects in response to a partner's defection results in the same behavior as does the strategy of a habitual cooperator, despite possessing different response rules. The potential defector is never induced to defect and the habitual cooperator always cooperates and thus only cooperative behavior is seen. In biological terms the strategies have different genotypes but the same phenotype, which corresponds to the difference between latent and observed behavior in social systems. As a result cooperative behavior may occur even when the strategies involved include non-cooperative rules, if these rules are not activated. The types of strategies produced by group selection and individual selection differ noticeably, with group selection strategies having the following characteristics compared to individual selection strategies:

4.2.1. Think nice

Comparison of the fictitious history, positions $H_{t\text{-}3}$, $H_{t\text{-}2}$ and $H_{t\text{-}1}$ of Table 1 shows more Cs. Group selection strategies commence the game with a more cooperative predisposition, which is represented by being more likely to assume a history of cooperation.

4.2.2. Act nice

In general, the strategies emerging from group selection are less likely to defect in response to a given pattern of behavior than those emerging from individual selection. In particular, in group selection they are more likely to cooperate after three successive defections (55.5% versus 30.8%), which avoids getting caught in infinite cycles of defection. Players are more likely to continue to cooperate when the pattern is repeatedly cooperative, when a defection is followed by two cooperations or three successive cooperations, and are more forgiving, being more prepared to cooperate when the other cooperates after two previous defections (58% versus 26.4%).

4.2.3. Provocable

Strategies emerging from group selection are not naive cooperators, as they are just as likely as those emerging from individual selection to retaliate once the other starts to defect, which is reflected in responses to D,C,D and C,D,D.

Strategies from group selection have much in common with the characteristics of successful strategies identified by Axelrod (1984) in an IPD setting: nice, provocable, forgiving and clear.

Table 1
Probability of cooperating for strategies with memory length three in the final generation under group and individual reward mechanisms.*.

Position	H_{t-3}	H_{t-2}	H_{t-1}	(D,D,D)	(D,D,C)	(D,C,D)	(D,C,C)	(C,D,D)	(C,D,C)	(C,C,D)	(C,C,C)
Group	61.9*	83.3*	88.7	55.5*	58.0*	48.8	84.1*	49.8	55.6*	54.1*	98.9*
Individual	54.1*	56.1*	86.0	30.8*	26.4*	53.4	67.0*	48.0	71.9*	62.3*	77.6*

*Results are for a Prisoners Dilemma game with CC = 0.5, CD = 0.1, DC = 0.7 and DD = 0.2. First three cells contain the fictitious history whilst the remaining eight contain the percentage of players' who cooperate in response to the observed history. For each entry if the difference in proportions cooperating under the two selection and reward mechanism was significant at the 99% level (based on a Z-test) they are indicated with a *.

4.3. Hybrid section rules

The results in the previous section compared group and individual selection. Whilst group selection appears to outperform individual selection in many circumstances, group section may not fully differentiate between rewarding self-sacrificing behavior (good) and rewarding free riding behavior (bad). Free riders may survive in a group over extended periods of time and have a negative impact on group performance. For example, van Dijk, Sonnemans, and van Winden (2001) show experimentally how the extra effort induced in some individuals by team based rewards may be lost due free riders in the group. A variety of approaches for dealing with this have been considered, including punishment (Gachter & Fehr, 2000) and allowing individuals a say in who they interact with (Page, Putterman, & Unel, 2005). An alternative is for firms to mix group rewards that encourage cooperation with individual incentives encouraging effort, although Libby and Thorne (2009) suggest that such incentive systems may confuse agents, even though situations exist in which they produce superior results. In the simulations group and individual mechanisms differ in two important dimensions - the way in which performance is calculated, either the individual or the group scores, and the formation of groups. Group selection retains the best performing groups in their entirety whilst individual selection does not. Additional simulations were conducted to examine the effects of different mixes of group and individual selection. First, a two dimensional space of selection schemes was developed, in which the weight given to individual and group performance varies along one dimension and degree of group mixing on the other. For the performance dimension the performance of an individual U_i in a group k, is given by the following formula:

$$U_i = (1-\alpha)S_i + \alpha\frac{G_k}{n/m} \quad (1)$$

Where S_i is individual i's performance and G_k the total performance of group k, $G_k/(n/m)$ is the average score of each member of the group, the weight given to average group performance is α and the weight given to individual performance is 1- α. U_i is therefore a mixture of individual and group performance controlled by α. The second dimension is the degree of group mixing, β. With probability β, each individual whose performance is greater than or equal to the population median remains in the same group in the new generation. With probability $1-\beta$, they are moved to another group selected at random and replaced by new individuals generated by mutation and crossover of those individuals that survived the previous generation. Individuals whose performance is below the population median are removed from their groups and the population. This procedure means that if $\beta = 0$ the next population is randomly mixed whilst if $\beta = 1$ the population structure is maintained with those individuals who performed less than their group median replaced by new strategies. Simulations were done for all combinations of α and β, where $\alpha, \beta \in \{0.0, 0.1\ldots0.9, 1.0\}$. If $\alpha = 1$ and $\beta = 1$ the model matches group selection as presented in the previous section, while if $\alpha = 0$ and $\beta = 0$ the model corresponds to individual selection. The simulations in each case were repeated 1000 times, the same as in the earlier simulations.

Fig. 3 shows the best performing individual and group scores for the space of selection mechanisms averaged over all games, where CC, DC, CD, DD $\in\{0.0, 0.1,., 0.9, 1.0\}$. The results show that pure group selection rules maximize individual performance. Hybrid rules do not enhance individual performance. Higher levels of β increase the best scores but this effect is secondary to that of α. Group performance increases with both α and β and the maximum occurs when $\alpha = 1$ and $\beta = 1$. Pure group selection on average produces better performing individuals and groups than does either individual selection or hybrid rules. This shows that both group based selection and a stable group mix contribute to this effect.

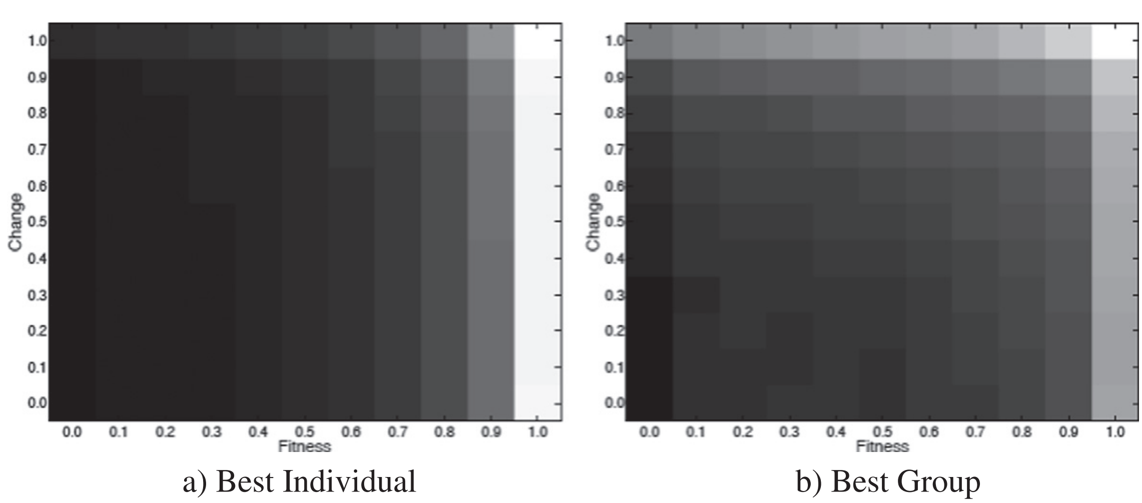

Fig. 3. Best individual and group performance across the space of selection and reward mechanisms.*. *All results averaged over 14641 games for the best individual and group performance in the final generation of each simulation. The performance measure, α, ranging from 0.0 (individual based evaluation) to 1.0 (group based evaluation) is given on the x-axis. The group mixing measure, β, ranging from 0.0 (random) to 1.0 (constant) is given on the y-axis. Lighter colours represent higher scores.

Table 2
Performance matrices for three sample interaction games (row player performance, column player performance).

	C	D
(a) Game 1		
C	0.5,0.5	0.1,0.7
D	0.7,0.1	0.2,0.2
(b) Game 2		
C	0.5,0.5	1.0,1.0
D	1.0,1.0	0.1,0.1
(c) Game 3		
C	0.5,0.5	0.0,0.3
D	0.3,0.0	0.6,0.6

The results shown in Fig. 3 show the overall pattern, which is similar to the results of earlier analysis highlighting the types of games where individual selection is superior. To examine this further consider the effect of α and β on three specific games. The performance matrices are shown in Table 2. For Game 1 (Prisoners Dilemma), the previous results showed group selection produces both the best performing individuals and groups. In Game 2 group selection produces the best performing groups but individual selection produces the best individuals. For Game 3 individual selection produces the best individuals and groups.

Fig. 4 shows the results for the three games under the different selection mechanisms. For Game 1, the Prisoners Dilemma, the highest average performance occurs at high levels of α and any level of β. High α means that the reward for individual performance is principally determined by the overall group performance, which rewards co-operators. This being the case, β becomes unimportant – group structure being maintained or new groups being formed from the successful co-operators has no effect. The best individuals for these parameter combinations also perform relatively better but they are outperformed by the best individuals under high β and intermediate α. In this setting, rewards for an individual are dependent on their own performance as well as the group's. If one individual in a group occasionally defects they increase their own performance with relatively little effect on the group reward component of their performance. This is only the case if β is high. If population shuffling results in defectors coming together they potentially perform very badly, damaging group performance.

In Game 2 individual selection produces the best performing individuals and group selection the best performing groups. As noted before, the highest individual performance occurs when a player is part of a group in which the majority uses the opposite strategy and this occurs more frequently under individual selection. The analysis of α and β in Fig. 4 shows that both contribute to this effect. More population mixing ensures that these chance pairings happen more frequently whilst an individual reward component means that high performing individual strategies will spread in the population, changing the numbers of cooperators and defectors and making unbalanced groups more likely. Panel D shows that the key element leading to better performing groups under group selection is high β, that is, stable group structure. In this game the highest performance is achieved when cooperators play defectors in equal numbers. Stable groups are better able to do this than those that are randomly mixed. Here α has a weak effect, particularly at high β but for lower values of β, performance decreases with increasing α – the same pattern observed for the best performing individual.

The results for Game 3 show that β has very little effect on performance and the apparent superiority of individual selection comes from α. In other words, group structure is unimportant but individual reward components are beneficial. This follows from the justification provided above for superior individual performance in these games. Individual based selection aids individuals, and therefore the population, to move from inferior equilibria to superior ones. The results show that this happens in response to only a small individual reward component. Whether individuals are mixed or the population structure is maintained has little effect on this.

5. Discussion and conclusions

Whilst prior research highlights the positive effect on performance of cooperation within work groups and teams, little work considers how to develop and maintain this cooperation. The results reported here provide a systematic basis for understanding the conditions under which work group based evaluation and reward systems lead to higher group and individual performance relative to individually oriented systems. The results show that group selection: a) produces higher individual and group performance for a wider range of games than does individual selection; b) dominates in games where group and individual performances are not aligned; and c) leads to the emergence and survival of groups of strategies in which some individuals perform far better than others and the group as a whole performs better. Individual selection only does better when group and individual performance incentives are aligned. In other words when the best performing strategy for an individual also produces the highest group performance, as reflected in the sentiment what is good for General Motors is good for America! In this situation, unilateral deviation, in which one player moves to a collectively lower but individually higher payoff, aids group performance. This type of task is a pure individual design with no interdependence among group members, tasks are performed independently and do not depend on the performance of others. This is in line with Wageman's (1995) experiments with work groups, which showed that independence can produce high performance. Seldom, however, do group tasks have this characteristic. The use of hybrid rules, those rewarding both individual and group performance, does not change this key finding. The best performing groups and individuals still occur when rewards are determined purely on group performance and group structure is maintained.

The results have implications for the design of group tasks and incentive schemes in firms and, by extension, they are relevant also for the development of industries, business networks and regions because they are groups of individual firms and other organizations.

First, the findings show the need to match incentive schemes with group tasks and interconnected work flows because this results in interdependent individuals in the group. Identifying such group situations requires a careful examination of the degree to which individual and group performance is aligned. The degree of alignment reflects different types of task interdependence, such as those described by Thompson (1967) and Van de Ven et al. (1976). For example, the Prisoners' Dilemma game, in which group selection performed best, is a form of pooled task interdependence (Thompson, 1967), whilst a second game in which individual selection performed best resembles a form of serial task interdependence. Another type of interdependence is reciprocal interdependence in which the output of each worker is the input of the other. Here, mutual cooperation dominates as DC and CD harm the performance of both parties and DD means nothing is done. In this situation group and individual selection do equally well. The general form of the problem investigated here is task interdependence (Van de Ven et al., 1976) where interdependences exist between the tasks of all individuals in a group.

These findings call into question the conventional wisdom and common practice in which work group formation and reward structures favor rewarding the best performing individuals, or in other contexts, rewarding the best performing individual firms in an industry, network or region (Wilkinson, Mattsson, & Easton, 2000). The findings indicate that managers (or policy makers) need to rethink and redesign group tasks in order to change interdependencies as well as the design of incentive systems. As Sutton (2007) notes, a focus exclusively on individual incentives is likely to damage group functioning as this over-rewards the most visible performers, under-rewards those who support

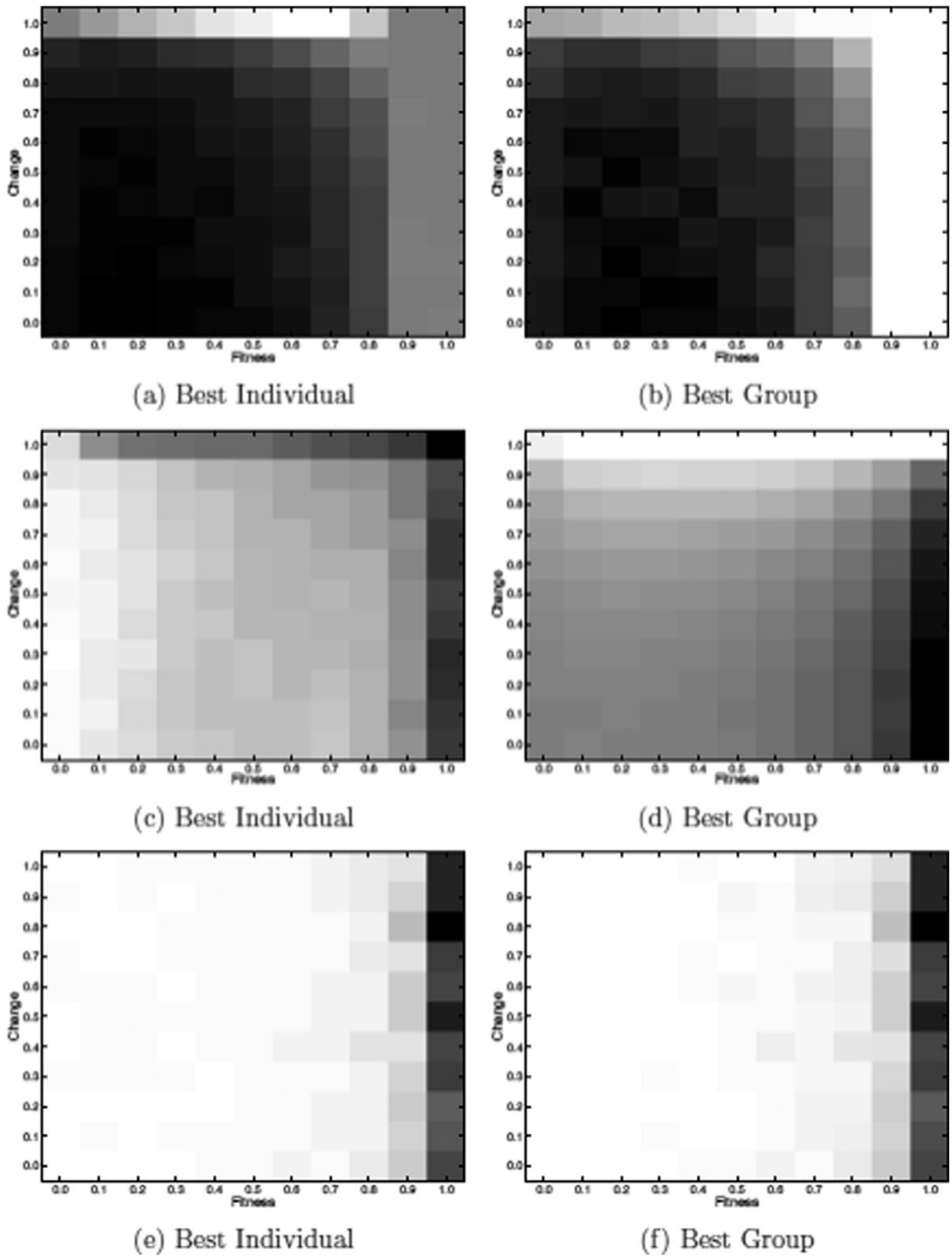

Fig. 4. Best individual and best group performance for three interaction games+ across the space of selection and reward mechanisms.*. *All results averaged over 14641 games for the best individual and group performance in the final generation of each simulation. The performance measure, α, ranging from 0.0 (individual based evaluation) to 1.0 (group based evaluation) is given on the x-axis. The group mixing measure, β, ranging from 0.0 (random) to 1.0 (constant) is given on the y-axis. Lighter colours represent higher scores. +Games: Panels (a) and (b): CC = 0.5, CD = 0.1, DC = 0.7, DD = 0.2. Panels (c) and (d): CC = 0.5, CD = 1.0, DC = 1.0, DD = 0.1. Panels (e) and (f): CC = 0.5, CD = 0.0, DC = 0.3, DD = 0.6.

them and fails to include in the metrics the costs and damages associated with favoring the top performers.

Second, the results provide support for previous empirical research. For example, Libby and Thorne (2009) showed that group incentives have no effect on production line tasks when little interaction takes place, or, in other words when the interdependencies are very low such that one worker's performance has little effect on another's, thereby aligning individual and group performance. Similarly, research has shown that group cohesion and shared knowledge and cognitions, which aid coordination processes, have a greater effect on group effectiveness when the group task involves more complex work flows, which make group members more interdependent (Kozlowski & Ilgen, 2006). Greater levels of interdependence create more opportunities for conflicts of interests to arise and misalignment between individual and group performance. In such situations group reward mechanisms produce superior outcomes.

A counter intuitive result is that group evaluation and reward systems not only produce superior group performance for most games, they also produce the best performing individuals. This is because the mix or ecology of strategies arising in a group supports and sustains high performing individuals, whose strategies contribute to higher overall group performance. Individual based systems select high performing individuals and they become more frequent in groups. This means they have to interact more with each other, leading to interactions that tend to reduce their own, as well as the group's performance. Referring to an earlier example, this is why individual selection of hens laying the most eggs produced mean, aggressive hens and lower overall performance compared to group selection (Muir, 1996). This result conflicts with empirical research indicating that feedback focused on team performance tends to yield better team performance at the expense of individual performance (DeShon, Kozlowski, Schmidt, Milner, & Wiechmann, 2004). This may be due to the type of group task and interdependencies studied.

Third, the results show that for many types of iterated games no significant differences exist between the results for individual and group selection. This result is valuable because the finding helps managers to focus on work group situations in which the evaluation and reward mechanism matters. The results show that they matter when group and individual performance are not aligned. In practice, determining the degree of alignment between individual and group interests may be difficult to determine. A variety of interaction effects may co-exist in a group and change over time, such that individual and group interests are sometimes but not always aligned. This suggests the need for careful monitoring and varying of individual and group incentives over time. The results provide some guidance in the analysis and classification of work group conditions and also indicate the types of real world experiments required to test the effect of different incentive systems, rather than having to do this for all types of conditions.

Fourth, the results provide new insights into the nature and effects of free riders in groups, those who benefit from the strategies of others at the expense of group performance. Much research on cooperation in groups has focused on the problem of free riders or social loafers (Kozlowski & Ilgen, 2006). The types of cooperative strategies that emerge and survive under group based incentive systems are difficult to exploit by free riders. This is because they have characteristics similar to that of Tit-for-Tat, the winning strategy under individual selection found by Axelrod and Hamilton (1981). Individuals using this type of strategy are nice in that they begin by cooperating and are not the first to defect; they are more forgiving, quickly returning to cooperation after a defection; and they are easy to recognize and understand. But they are also provocable because they quickly respond to defection by defecting themselves. While free riders may survive longer under group selection at the expense of the group's performance they will be eliminated eventually because they compromise the performance of groups in which they operate and such groups will be selected out. In practice, other group members are likely to identify free riders and punish them for their behavior because of their effect on group performance.

Fifth, an important and novel result is identifying a new type of role in groups, self-sacrificers, which have important implications for group design and reward systems. They are not the same as free riders, who exploit group behavior at the expense of the group. Self-sacrificers help to improve group performance at their own expense and are instrumental in producing superior group performance, even though their individual performance is poor. This situation occurs when mixed strategies, in other words DC and CD, lead to better group performance rather does all Cs or all Ds. Here, the performance may be strongly asymmetric with the Ds looking like star workers and the Cs like dogs. But if self-sacrificers are removed from the group, punished, learn to or are forced to change their behavior, overall performance suffers because the group is no longer able to co-produce the star performers. One possible example that suggests itself is university departments and the way performance is assessed and rewarded. Universities tend to assess academic performance and rewards based on an individual's research publications. But an individual's research output in part depends on the behavior of others in the department, whose individual research performance may be weak. These could be those willing and able to take on more of the less attractive and poorly rewarded tasks, such as additional administration and teaching, at the expense of their own research and publications. Their behavior enables others to become more research productive and the research performance of the department as a whole improves. If rewards only go to research stars and poor performers are not rewarded, or encouraged to leave, the behavior of and types of people in the department changes. As a result the stars make up more of the department but they then start to compete with each other, which may damage each other's research performance and compromise teaching and administrative duties. Overall levels of cooperation and morale in the department diminish, which also eventually impacts on research, as well the ability of the department to attract and retain potential stars. A better solution, based the results described here, is including some rewards for the department as a whole that help build a productive mix or ecology of research, teaching and administration-focused academics that co-produces, as well as retains research stars. One corollary of this type of reasoning is that high performing research departments may have more non or low performing researchers than others! This would be an interesting proposition to test.

Several possible extensions of the computational approach used here exist. These include varying the mix of games in a group, as well as considering the effects of different types of interaction networks within and between groups. In the model used here all the players play the same iterated game. Future research could examine the effects of different mixes of games co-existing, especially in terms of the degree of alignment of group and individual performance. Also, here players play all the players in their group and none of those in other groups. Future research could examine the effects of different networks of interaction and ones that change over time due to individuals choosing and refusing who to interact with. Extensions such as these will enable the modeling of more complex and nuanced group structures and even the ability to mimic more closely particular examples of actual complex work group situations.

Another extension is to examine the effects of using ways other than genetic algorithms to model evaluation and reward systems. These include modeling the processes in terms of the individual learning and adaption mechanisms and social influence processes among individuals.

This paper also presents an opportunity to design experiments, both in laboratories and firms, that empirically test the implications of this research. These results can help direct attention to the most productive types of experiments to design; ones that focus on key kinds of differences between work groups, such as the degree to which individual and group performance are aligned. Further the research results indicate that interactions among all members of a group matter in determining performance. Yet most reported experiments and mathematical models of the effects of incentives on work groups and teams do not take into account these interdependencies and the possibility of group effects. Experiments mix participants randomly and do not allow participants to know the identity of those they play against over time, see for example Kalra and Shi (2001) and Lim et al. (2009). This allows many opportunities for further research that include different types of interdependencies among group members, that allow for changes in group composition and patterns of interaction over time, the emergence of relationships and cooperative behavior among group members and specialization.

As indicated above, computational social science methods can help in addressing many of these research issues.

To summarize, the research reported here provides valuable and novel insights into the nature, role and impact of individual versus group evaluation and reward systems on the behavior and performance of work groups. The findings show that group based schemes produce better performing groups and individuals in many situations and they reveal the existence of a new type of role, the self-sacrificer, who plays a key role in improving the performance of the group as a whole at their own expense. Such individuals do not emerge and remain when individual based evaluation and reward systems operate. In addition, the research demonstrates the potential value of a different type of research methodology, computational social science, in which agent based computer simulation models are used to model, in more realistic ways than conventional linear models, key dimensions of work group behavior. These models are subjected then to systematic experiments examining the behavior of the model over time under different conditions in order to determine their effects. The potential value of this approach is not limited to the study of work groups, the approach can be used to better model and understand the behavior all types of complex nonlinear systems, including work group, teams, firms, industries, business relations and networks, supply chains and whole economic and market systems. As noted earlier, the potential value of computational social science methods are gaining increased attention in many disciplines, including business related ones, such as management and marketing. These methods open up many new opportunities for future research.

References

Aimea, F., Meyer, C. J., & Humphrey, S. E. (2010). Legitimacy of team rewards: Analyzing legitimacy as a condition for the effectiveness of team incentive designs. *Journal of Business Research*, *63*(1), 60–66.

Akerlof, G. A., & Kranton, R. E. (2005). Identity and the economics of organizations. *The Journal of Economic Perspectives*, *19*(1), 9–32.

Arya, A., Fellingham, J., & Glover, J. (1997). Teams, repeated tasks, and implicit incentives. *Journal of Accounting and Economics*, *23*(1), 7–30.

Ashlock, D., Smucker, M. D., Stanley, E. A., & Tesfatsion, L. (1996). Preferential partner selection in an evolutionary study of prisoner's dilemma. *Biosystems*, *37*(1), 99–125.

Axelrod, R. (1984). *The evolution of cooperation*. New York: Basic Books.

Axelrod, R. (1987). The evolution of strategies in the iterated prisoner's dilemma. In L. Davis (Ed.), *Genetic algorithms and simulated annealing* (pp. 32–41). London: Pitman.

Axelrod, R. (1997). Advancing the art of simulation in the social sciences. In R. Conte, R.H., & P. Terna (Eds.), *Simulating social phenomena* (pp. 21–40). Berlin: Springer.

Axelrod, R., & Hamilton, W. D. (1981). The evolution of cooperation. *Science*, *21*(1), 1390–1396.

Beersma, B., Hollenbeck, J. R., Humphrey, S. E., Moon, H., Conlon, D. E., & Ilgen, D. R. (2003). Cooperation, competition, and team performance: Toward a contingency approach. *Academy of Management Journal*, *46*(5), 572–590.

Bowles, S., Choi, J. -K., & Hopfensitz, A. (2004). The co-evolution of individual behaviors and social institutions. *Journal of Theoretical Biology*, *223*, 135–147.

Chan, T. Y., Li, J., & Pierce, L. (2014). Compensation and peer effects in competing sales teams. *Management Science*, *60*(8), 1965–1984.

Chang, M. H., & Harrington, J. E. (2006). Agent-based models of organizations. In L. Tesfatsion, & K. L. Judd (Eds.), *Handbook of Computational Economics*, *2*. (pp. 1273–1337). Amsterdam: Elsevier.

Che, Y. -K., & Yoo, S. -W. (2001). Optimal incentives for teams. *American Economic Review*, *91*(3), 525–541.

Cummings, J. N. (2004). Work groups, structural diversity, and knowledge sharing in a global organization. *Management Science*, *50*(3), 352–364.

Cummings, J., & Cross, R. (2003). Structural properties of work groups and their consequences for performance. *Social Networks*, *25*(3), 197–210.

D' Alessandro, S., & Winzar, H. (2014). Special issue on complex systems: Editor's forward. *Australasian Marketing Journal*, *21*(2), 2–3.

de Jong, A., de Ruyter, K., & Wetzels, M. (2005). Antecedents and consequences of group potency: A study of self-managing service teams. *Management Science*, *51*(11), 1610–1625.

Deissenberg, C., van der Hoog, S., & Dawid, H. (2008). Eurace: A massively parallel agent-based model of the European economy. *Applied Mathematics and Computation*, *204*(2), 541–552.

DeShon, R. P., Kozlowski, S. W. J., Schmidt, A. M., Milner, K. R., & Wiechmann, D. (2004). A multiplegoal, multilevel model of feedback effects on the regulation of individual and team performance. *Journal of Applied Psychology*, *89*, 1035–1056.

Ellis, A. P., Hollenbeck, J. R., Ilgen, D. R., Porter, C. O., West, B. J., & Moon, H. (2003). Team learning: collectively connecting the dots. *Journal of Applied Psychology*, *88*(5), 821–835.

Encinosa, W. E., III, Gaynor, M., & Rebitzer, J. B. (2007). The sociology of groups and the economics of incentives: Theory and evidence on compensation systems. *Journal of Economic Behavior and Organization*, *62*(2), 187–214.

Epstein, J. M. (2006). Remarks on the foundations of agent-based generative social science. In L. Tesfatsion, & K. L. Judd (Eds.), *Handbook of Computational Economics*, *vol. 2*. (pp. 1585–1604). Amsterdam: Elsevier.

Ethiraj, S. K., & Levinthal, D. (2004). Bounded rationality and the search for organizational architecture: An evolutionary perspective on the design of organizations and their evolvability. *Administrative Science Quarterly*, *49*(3), 404–437.

Fehr, E., & Fischbacher, U. (2002). Why social preferences matter – the impact of non-selfish motives on competition cooperation and incentives. *The Economic Journal*, *112*, 1–33.

FitzRoy, F. R., & Kraft, K. (1987). Cooperation, productivity, and profit sharing. *Quarterly Journal of Economics*, *102*(1), 23–35.

FitzRoy, F. R., & Kraft, K. (1995). On the choice of incentives in firms. *Journal of Economic Behavior and Organization*, *26*(1), 145–160.

Fosco, C., & Mengel, F. (2011). Cooperation through imitation and exclusion in networks. *Journal of Economic Dynamics and Control*, *35*(5), 641–658.

Gachter, S., & Fehr, E. (2000). Cooperation and punishment in public goods experiments. *American Economic Review*, *90*(4), 980–994.

Garcia, R., & Jager, W. (2011). Introductory special issue on agent-based modeling of innovation diffusion. *Journal of Product Innovation and Management*, *28*, 148–151.

Gilbert, N., & Troitzsch, K. G. (2005). *Simulation for the social scientist*. Berkshire, UK: Open University Press.

Gilbert, N., Wander, J., Deffant, G., & Adjali, I. (2007). Complexities in markets: Introduction to the special issue. *Journal of Business Research*, *60*(8), 813–815.

Goette, L., Huffman, D., & Meier, S. (2006). The impact of group membership on cooperation and norm enforcement: Evidence using random assignment to real social groups. *The American Economic Review*, *96*(2), 212–216.

Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the network: a complex systems look at the underlying process of word-of-mouth. *Marketing Letters*, *12*(3), 211–223.

Gratton, L., & Erickson, T. J. (2007). 8 ways to build collaborative teams. *Harvard Business Review*, *85*(11), 100–109.

Hamilton, B. H., Nickerson, J. A., & Owan, H. (2003). Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation. *Journal of Political Economy*, *111*(3), 465–497.

Hammerstein, P. (2003). Understanding cooperation: an interdisciplinary challenge. In P. Hammerstein (Ed.), *Genetic and cultural evolution of cooperation* (pp. 1–6). Cambridge, Mass: MIT Press.

Harrison, J. R., Lin, Z., Carroll, G. R., & Carley, K. M. (2007). Simulation modeling in organizational and management research. *Academy of Management Review*, *32*(4), 1229–1245.

Held, F., Wilkinson, I. F., Young, L. C., & Marks, R. (2014). Agent-based modelling: a new type of research. *Australasian Marketing Journal*, *22*(1), 4–14.

Henrich, J. (2004). Cultural group selection, co-evolutionary processes and large-scale cooperation. *Journal of Economic Behavior and Organization*, *53*(1), 3–35.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., et al. (2001). In search of homo economicus: behavioral experiments in 15 small-scale societies. *American Economic Review*, *91*(2), 73–78.

Henrich, J., Ensminger, J., McElreath, R., Barr, A., Barrett, C., Bolyanatz, A., et al. (2010). Markets, religion, community size and the evolution of fairness and punishment. *Science*, *327*, 1480–1484.

Holland, J. H. (1975). *Adaption in natural and artificial systems*. University of Michigan Press.

Ilgen, D. R., & Sheppard, I. (2001). Motivation in teams. In M. Erez, U. Kleinbeck, & H. Thierry (Eds.), *Work Motivation in the context of a globalizing economy* (pp. 169–179). New York: Erlbum.

Jackson, E. A. (1996). The second metamorphosis of science: A second view (SFI Working Paper No. 96-05-059). *Santa Fe Institute*.

Jacobson, M., & Wilensky, U. (2006). Complex Systems in Education: Scientific and Educational Importance and Implications for the Learning Sciences. *Journal of the Learning Sciences*, *15*(1), 1–34.

Johnson, M. D., Hollenbeck, J. R., Humphrey, S. E., Ilgen, D. R., Jundt, D., & Meyer, C. J. (2006). Cutthroat cooperation: Asymmetrical adaptation to changes in team reward structures. *Academy of Management Journal*, *49*(1), 103–119.

Kalra, A., & Shi, M. (2001). Designing optimal sales contests: A theoretical perspective. *Marketing Science*, *20*(2), 170–193.

Katzenbach, Jon, & Khan, Z. (2010). *Leading outside the lines*. Strategy and Business, April 26 Issue 59.

Kozlowski, S. W. J., & Bell, B. F. (2003). Work groups and teams in organizations. In W. C. Borman, D. R. Ilgen, & R. J. Klimoski (Eds.), *Handbook of psychology: Industrial and Organizational Psychology*, *vol. 12*. (pp. 333–375). New York: Wiley-Blackwell.

Kendall, G., Yao, X., & Chong, S. Y. (2007). *The iterated prisoners' dilemma: 20 years on*. Inc.: World Scientific Publishing Co.

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological Science in the Public Interest*, *7*(3), 77–124.

Kvaløy, O., & Olsen, T. E. (2012). The rise of individual performance pay. *Journal of Economics & Management Strategy*, *21*(2), 493–518.

Lavy, V. (2002). Evaluating the effect of teachers' group performance incentives on pupil achievement. *Journal of Political Economy*, *110*(6), 1286–1317.

Lazer, D., & Friedman, A. (2007). The network structure of exploration and exploitation. *Administrative Science Quarterly*, *52*(4), 667–694.

Leombruni, R., & Richiardi, M. (2005). Why are economists skeptical about agent-based simulations? *Physica A*, *355*(1), 103–109.

Libby, T., & Thorne, L. (2009). The influence of incentive structure on group performance in assembly lines and teams. *Behavioral Research in Accounting*, *21*(2), 57–72.

Lim, N., Ahearne, M. J., & Ham, S. H. (2009). Designing sales contests: Does the prize structure matter? *Journal of Marketing Research*, *46*(3), 356–371.

Macy, M. W., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology*, 143–166.

Matros, A. (2012). Altruistic versus egoistic behavior in a public good game. *Journal of Economic Dynamics and Control*, *36*(4), 642–656.

May, R. M. (1976). Simple mathematical models with very complicated dynamics. *Nature*, *261*(5560), 459–467.

McNamara, J. M., Barta, Z., & Houston, A. I. (2004). Variation in behaviour promotes cooperation in the Prisoner's Dilemma game. *Nature*, *428*(6984), 745–748.

Midgley, D. F., Marks, R. E., & Cooper, L. C. (1997). Breeding competitive strategies. *Management Science*, *43*, 257–275.

Muir, W. M. (1996). Group selection for adaptation to multiple-hen cages: selection program and direct responses. *Poultry Science*, *75*(4), 447–458.

Muir, W. M. (2005). Incorporation of competitive effects in forest tree or animal breeding programs. *Genetics*, *170*, 1247–1259.

Nalbantian, H. R., & Schotter, A. (1997). Productivity under group incentives: An experimental study. *American Economic Review*, *87*(3), 314–341.

Page, T., Putterman, L., & Unel, B. (2005). Voluntary association in public goods experiments: Reciprocity, mimicry and efficiency. *The Economic Journal*, *115*(506), 1032–1053.

Prietula, M., Carley, K., & Gasser, L. (1998). *Simulating organizations: computational models of institutions and groups*. Cambridge, MA: MIT Press.

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for Rigor. *International Journal of Research in Marketing*, *23*(3), 167–280.

Rapoport, A., & Guyer, M. (1966). A taxonomy of 2×2 games. *General Systems*, *11*, 203–214.

Riechmann, T. (2001). Genetic algorithm learning and evolutionary games. *Journal of Economic Dynamics and Control*, *25*(6–7), 1019–1037.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *1*(2), 143–186.

Selten, R., & Warglien, M. (2007). The emergence of simple languages in an experimental coordination game. *Proceedings of the National Academy of Sciences*, *104*(18), 7361–7366.

Siebers, P. -O., & Wilkinson, I. F. (2013). Editorial: mult-agent simulation as a novel decision support tool for innovation and technology management. *International Journal of Innovation and Technology Management*, *10*(5), 1–4.

Stephens, D. W., McLinn, C. M., & Stevens, J. R. (2002). Discounting and reciprocity in an iterated prisoner's dilemma. *Science*, *298*(5601), 2216–2218.

Sutton, R. (2007, May). *Building the civilised workplace*. McKinsey quarterly (online).

Tesfatsion, L., & Judd, K. L. (Eds.). (2006). *Handbook of computational economics: agent-based computational economics*, *vol. 2*, Elsevier.

Thompson, J. D. (1967). *Organizations in action*. New York: McGraw Hill.

Trusov, M., Rand, W., & Joshi, Y. V. (2013). Improving prelaunch diffusion forecasts: using synthetic networks as simulated priors. *Journal of Marketing Research*, *50*(6), 675–690.

Van de Ven, A. H., Delbecq, A. L., & Koenig, R., Jr. (1976). Determinants of coordination modes within organizations. *American Sociological Review*, 322–338.

van Dijk, F., Sonnemans, J., & van Winden, F. (2001). Incentive systems in a real effort experiment. *European Economic Review*, *45*(2), 187–214.

Wageman, R. (1995). Interdependence and group effectiveness. *Administrative Science Quarterly*, *40*(1), 145–180.

Weber, R. A., & Camerer, C. F. (2003). Cultural conflict and merger failure: An experimental approach. *Management Science*, *49*(4), 400–415.

Weber, J., Holmes, S., & Palermi, C. (2005). The corporate innovation. *Business week* (pp. 79–80).

Wilkinson, I. F., Mattsson, L. G., & Easton, G. (2000). International competitiveness and trade promotion policy from a network perspective. *Journal of World Business*, *35*(3), 275–299.

Wilson, D. S., & Gowdy, J. M. (2013). Evolution as a general theoretical framework for economics and public policy. *Journal of Economic Behavior & Organization*, *90*, S3–S10.

Wilson, E. O., & Sober, E. (1994). Reintroducing group selection to the human behavioral sciences. *Behavioral and Brain Sciences*, *17*, 585–654.

Woodside, A. G., & Zhang, M. (2013). Cultural diversity and marketing transactions: Are market integration, large community size, and world religions necessary for fairness in ephemeral exchanges? *Psychology & Marketing*, *30*(3), 263–276.