Evolutionary dynamics of group fairness

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HIGHLIGHTS

- Agreements often involve group decisions where fairness may play a key role.
- This can be addressed through a multiplayer generalization of the Ultimatum Game.
- We show that imposing consensuses raises the proposals, leading to fairer agreements.
- Stochastic effects are shown to further enhance group fairness.

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ABSTRACT

The emergence and impact of fairness is commonly studied in the context of 2-person games, notably the Ultimatum Game. Often, however, humans face problems of collective action involving more than two individuals where fairness is known to play a very important role, and whose dynamics cannot be inferred from what is known from 2-person games. Here, we propose a generalization of the Ultimatum Game for an arbitrary number of players – the Multiplayer Ultimatum Game. Proposals are made to a group of responders who must individually reject or accept the proposal. If the total number of individual acceptances stands below a given threshold, the offer will be rejected; otherwise, the offer will be accepted, and equally shared by all responders. We investigate the evolution of fairness in populations of individuals by means of evolutionary game theory, providing both analytical insights and results from numerical simulations. We show how imposing stringent consensuses significantly increases the value of the proposals, leading to fairer outcomes and more tolerant players. Furthermore, we show how stochastic effects – such as imitation errors and/or errors when assessing the fitness of others – may further enhance the overall success in reaching fair collective action.

1. Introduction

Although evidence exists of collective action problems that other species engage on and successfully solve (Axelrod and Hamilton, 1981; Maynard-Smith and Price, 1973), humans are truly singular in the extent to which they resort to collective action (Barrett, 2003; Hardin, 1968; Henrich et al., 2001; Kollock, 1998; Levin, 2012; Ostrom, 1990). To this end they have developed highly sophisticated and unparalleled mechanisms (Apicella et al., 2012; Dietz et al., 2003; Fehr and Fischbacher, 2003; Fowler and Christakis, 2010; Gintis, 2000; Kollock, 1998; Nowak and Sigmund, 2005; Ohtsuki and Iwasa, 2004; Pacheco et al., 2009; Skyrms, 2004; Skyrms, 2010). Similar to

what happens when two individuals interact, also when groups get together to make collective decisions, the concept of fairness is known to play a very important role (Fehr and Schmidt, 1999; Fehr and Gächter, 2000; Henrich et al., 2001; Rabin, 1993). However, and in sharp contrast to the two-person interaction cases, where fairness has been given considerable attention, both theoretically (Binmore, 1998; Gintis et al., 2003; Nowak et al., 2000; Page and Nowak, 2002) and experimentally (Fehr and Schmidt, 2006; Henrich et al., 2001, 2010; Rand et al., 2013; Sanfey et al., 2003), the study of fairness in connection to group decisions has been limited to few investigations (Bornstein and Yaniv, 1998; Fischbacher et al., 2009; Messick et al., 1997; Robert and Carnevale, 1997).

The Ultimatum Game (**UG**) (Güth et al., 1982) has constituted the framework of choice (for an exception, see (Van Segbroeck et al., 2012)) with which to address the emergence and evolution of fairness in two-person interactions. In the two-person **UG** (and using common notation (Sigmund, 2010)), one individual plays the

role of the *Proposer* whereas the other individual plays the role of the *Responder*. The *Proposer* is endowed with an amount (without loss of generality, we may assume it is 1 unit) and makes an offer, which is a fraction *p* of that amount. We may assume that the *Responder* has an expectation value *q*, and will accept the proposal if the condition $p \geq q$ is satisfied, in which case the *Proposer* earns $1-p$ and the Responder earns *p*. In such a scenario, a fair offer corresponds to an equal split, that is $p = 1/2$.

Theoretical (Gale et al., 1995; Nowak et al., 2000; Page and Nowak, 2002; Rand et al., 2013) and experimental (Henrich et al., 2004; Henrich et al., 2001) investigations have shown that humans generally accept offers with $p \geq 0.4$, a feature which (with some variation) applies to both *old* and *new* societies, as a series of cross-culture studies have shown (Henrich et al., 2001). But what about group decisions? While there are no theoretical studies of the **UG** in a group context, there is one experiment (Messick et al., 1997) which naturally captures some limiting situations of the **M**ulti-Player **UG** (**MUG**) that we develop below, and which puts in evidence a small part of the plethora of new possibilities enacted by group decisions, with direct consequences in what concerns the concept of fairness. Naturally, we shall take the opportunity to compare our independent theoretical predictions with available results from the aforementioned behavioral experiments.

2. Model and methods

2.1. Multiplayer ultimatum games

Let us assume a large population of individuals, who assemble into groups of size *N*. Each individual has a strategy encoded by 2 real numbers $\{p, q\} \in [0, 1]$, whose significance is explained below. At any instance of the game, there will be 1 *Proposer* and $N-1$ *Responders*. Following the conventional notation of **UG** (Sigmund, 2010), the total amount initially given to the *Proposer* is equal to 1. The *Proposer* will offer an amount $p \in [0,1]$ corresponding to her/his strategy, whereas each of the $N-1$ *Responders* will accept or reject the offer based on each one's individual acceptance threshold given by $q \in [0,1]$. Thus, each *Responder* will individually state his acceptance (if $q \leq p$) or rejection (if $q > p$). Overall, the group acceptance is conditional on a minimum number of individual acceptances (*M*): if the number of individual acceptances stands below *M*, the offer will be rejected. Otherwise, the offer will be accepted. In the former case, no one earns anything, whereas in the latter case, the *Proposer* will keep $1-p$ to himself and the group will share the remainder, that is, each *Responder* gets $p/(N-1)$. Thus, in line with the **UG**, a fair split will be characterized by $p = 1-1/N$, as in this case both *Proposer* and *Responders* will get the same fraction of the endowment. In this context, we should also specify that *Empathy*, used in the 2-person **UG** to characterize those strategies where $p = q$ (Page and Nowak, 2002) that is, those individuals who will only accept split offers not below what they propose, is here also associated with strategies characterized by $p = q$.

Group aced in a variable a_i, assuming the value 1 if the proposal by individual *i* is accepted, and 0 otherwise:

$$a_i = \begin{cases} 1, & if \ \sum_{j=1, j \neq i}^{N} \Theta(p_i - q_j) \geq M \\ 0, & otherwise \end{cases} \tag{1}$$

where $\Theta(x)$ is the Heaviside function, assuming the value 0 when $x < 0$ and 1 otherwise. The average payoff Π_i earned by an individual *i* in a given group of *N* individuals, will be given by the average gain earned when a individual acts once as the *Proposer* – $\Pi_P = (1-p_i)a_i$ — and $N-1$ times as a *Responder* –$\Pi_R = (1/(N-1))\sum_{k=1, k \neq i}^{N} p_k a_k$, where p_k is the offer of individual *k* and a_k refers to the proposal of individual *k*. Individual *i* plays with $N-1$ opponents; if $N=2$ and $M=1$, the game played is the traditional 2-person **UG**. It is worth noting that the maximum payoff of individual *i* is obtained when p_i is the smallest possible and all other p_k (the opponents' offers) are maximized. Therefore, the pressure to *free-ride*, that is, offering less and expecting that others will contribute, should be very high. Furthermore, dividing the game in two stages and reasoning in a backward fashion, the conclusions regarding the *sub-game perfect equilibrium* of this game anticipate the use of the smallest possible p_i and q_i, irrespectively of *N* and *M*, thus mimicking the conclusions for the traditional 2-person **UG**. Following the well-mixed assumption, the fitness of one individual will be provided by the average payoff calculated over a big number of groups, randomly sampled from the population.

2.2. Evolutionary dynamics

Instead of revising their strategies through rational reasoning, Humans often resort to the experiences and successes of others to select their next move, as, in fact, has been shown to be the case in the context of public donations (Carman, 2003; Fowler and Christakis, 2010; Rees et al., 2009). Such an interacting dynamical process, grounded on peer-influence and imitation, creates a behavioral ecosystem in which strategies and behaviors evolve in time, whereas the returns of each individual depend on the actual frequency of each strategy present in the population. Here we adopt such social learning dynamics (Rendell et al., 2010; Santos and Pacheco, 2011; Sigmund et al., 2010; Tomasello and Call, 1997; Traulsen et al., 2006), which is also well suited to be used in the framework of evolutionary game theory. The baseline assumption is that individuals performing better when playing multiplayer **UG** (i.e. those achieving higher average payoffs) will be more often imitated and thus their behaviour will spread in the population. In other words, social success drives the evolution of strategies in the population. This dynamical process is implemented both analytically and in computer simulations.

2.3. Simulations

Our simulations start from a well-mixed population of size $Z = 1024$, much larger than the group size *N*. Individual strategy values of *p* and *q* are all drawn from a probability distribution obtained by discretizing a uniform distribution in the interval [0,1] into 101 equally spaced values. Simulations last for 4000 generations, and we consider that, in each generation, all the individuals have the opportunity to revise their strategy through imitation. At every (discrete and asynchronous) time step, two individuals *A* and *B* are randomly selected from the population and their individual fitness is computed, by averaging the payoff obtained from 10^4 randomly sampled groups of size *N*; subsequently, *A* copies the strategy of *B* with a probability χ which grows monotonously with the fitness difference $f_B - f_A$, following the pairwise comparison update rule (Traulsen et al., 2006) – $\chi = (1 + e^{-\beta(f_B - f_A)})^{-1}$. The parameter β conveniently specifies the selection pressure ($\beta = 0$ represents neutral drift and $\beta \to \infty$ represents a purely deterministic imitation dynamics). Additionally, when imitation occurs, the copied *p* and *q* values will suffer a perturbation due to errors in perception. The new strategy parameters will be given by $p' = p + \xi_p(\varepsilon)$ and $q' = q + \xi_q(\varepsilon)$, where $\xi_p(\varepsilon)$ and $\xi_q(\varepsilon)$ are uniformly distributed random variables drawn from the interval $[-\varepsilon, \varepsilon]$. This feature (i) models a slight blur in perception, (ii) helps to avoid the random extinction of strategies, and (iii) ensures a complete exploration of the strategy spectrum, given that the pairwise comparison does not introduce new strategies in the population (Vukov et al., 2011). Also, with probability μ, imitation will not occur and the individual will adopt random values of *p* and *q*, performing a random exploration of behaviors. For each combination of parameters, the simulations were repeated 50 times. We computed the average values of *p* and *q* by performing a time and ensemble

average, taken over all the runs and considering the last 25% of generations, disregarding the initial transient periods.

2.4. Analytical insights from a model based on the replicator dynamics

The analytical results we shall present and discuss in Section 3 were obtained employing the replicator dynamics (Hofbauer and Sigmund, 1998), which describes the frequency dependent evolutionary dynamics of infinite, well-mixed populations. Let x_i be the relative frequencies of a strategy i, and f_i the fitness of the same strategy. Then, the replicator equations read $\dot{x}_i = x_i(f_i - \bar{f})$, where $\bar{f}$ stands for the average fitness of the population. As $\sum x_i = 1$, the overall dynamics of a population with s strategies may be given by (numerically) solving a system of $s-1$ coupled, non-linear, ordinary differential equations. The replicator equations reflect a simple and intuitive dynamics for each strategy depending on whether the fitness of a given strategy is higher (lower) than the average fitness of the entire population: The frequency of individuals adopting that strategy will increase (decrease) in the total population. As all individuals are equally likely to interact, groups are randomly sampled from the population, which leads to group compositions that follow a multinomial distribution (Gokhale and Traulsen, 2010; Hauert et al., 2006; Pacheco et al., 2009; Sigmund, 2010).

In our case, we analyze the evolution of a limited strategy space made of $s=3$ paradigmatic strategies, obtained by considering two different values for both p and q – high (h) and low (l). In this restricted strategy space we still have 4 possible strategies – however, in the following we will disregard the Paradoxical strategy P corresponding to the combination $P = \{l, h\}$, as one can trivially show that this strategy is strictly dominated by any of the remaining 3. In the specific scenario of **MUG**, we use the following designation for the 3 strategies remaining strategies: The pro-Social strategy ($S = \{h, h\}$), the Asocial strategy ($A = \{l, l\}$), and the Generous strategy ($G = \{h, l\}$) (see below for details). Making use of this set of 3 strategies, we may write the average fitness of each strategy as

$$f_S(x_S, x_A) = \sum_{k_S=0}^{N-1} \sum_{k_A=0}^{N-1-k_S} \frac{(N-1)!}{k_S!k_A!(N-1-k_S-k_A)!}$$
$$x_S^{k_S} x_A^{k_A} (1 - x_S - x_A)^{N-1-k_S-k_A} \Pi_S(k_S+1, k_A),$$

$$f_A(x_S, x_A) = \sum_{k_S=0}^{N-1} \sum_{k_A=0}^{N-1-k_S} \frac{(N-1)!}{k_S!k_A!(N-1-k_S-k_A)!}$$

$$x_S^{k_S} x_A^{k_A} (1 - x_S - x_A)^{N-1-k_S-k_A} \Pi_A(k_S, k_A+1),$$

$$f_G(x_S, x_A) = \sum_{k_S=0}^{N-1} \sum_{k_A=0}^{N-1-k_S} \frac{(N-1)!}{k_S!k_A!(N-1-k_S-k_A)!}$$
$$x_S^{k_S} x_A^{k_A} (1 - x_S - x_A)^{N-1-k_S-k_A} \Pi_G(k_S, k_A),$$

where $\Pi_i(k_S, k_A)$ is the payoff that a player adopting a strategy $i = \{S, A, G\}$ receives in a group of size N, made of k_S S's, k_A A's and $N-k_S-k_A$ G's. These payoff functions read

$$\Pi_S(k_S, k_A) = 1 - h + \frac{(N-k_A-1)h+a(k_S)k_Al}{N-1},$$

$$\Pi_A(k_S, k_A) = (1-l)a(k_S) + \frac{(N-k_A)h+a(k_S)(k_A-1)l}{N-1},$$

$$\Pi_G(k_S, k_A) = 1 - h + \frac{(N-k_A-1)h+a(k_S)k_Al}{N-1}.$$

As high (h) proposals will always be accepted, only Asocial individuals are in danger of having their proposals rejected. Moreover, as only pro-Social individuals reject low proposals, and since a single Asocial Proposer is not able to accept his own proposal, the relevant number of acceptances will be $N-k_S-1$; thus, $a(k_S)$ summarizes the acceptance criteria – $a(k_S) = \Theta(N-k_S-1-M)$, in which $\Theta(x)$ defined before.

3. Results and discussion

The results of the numerical simulations are shown in Fig. 1, where we plot the average stationary values of p and q in the population (normalized by the corresponding values for $N=2$) as a function of the group size N, for two limiting group behaviors: $M=1$ (left panel) and $M=N-1$ (right panel). Thus, whereas the left panel shows how p and q evolve as a function of group size in situations in which offer acceptance by a single Responder is enough to ensure collective action, the right panel shows the corresponding evolution in situations in which a unanimous acceptance by all Responders is required before the group-split is accomplished.

We take as reference values the stationary values of p and q for the conventional (2 player) **UG**, with values $p=0.27$ and $q=0.11$, respectively. These reference values are influenced by the intensity of selection (β) and errors in imitation (ε), which, as discussed below (see also Rand et al., 2013), do influence the stationary values plotted for p and q. Fig. 1 clearly shows that the two limiting
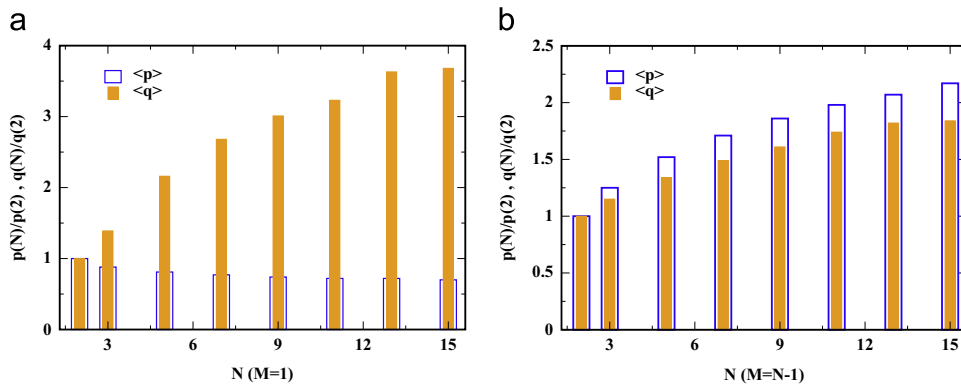

Fig. 1. Results for the (population wide) average values of p and q obtained as a result of computer simulations of the **MUG** in populations in which individuals start from a random distribution of strategies defined each by the duple $\{p, q\}$. We plot the values of p and q relative to the corresponding values for $N=2$ ($p=0.27$ and $q=0.11$, respectively). Solid bars display q-values, whereas hollow bars display p-values. Unlike the usual $N=2$ UG, in the **MUG** there are many cases that one may consider. The panels above explore 2 limiting cases: (a) the case in which it is enough that a single Responder accepts the offer for the split to be made, and (b) the case in which all Responders must accept the offer for the split to be made. These 2 opposite limits converge to a single case for $N=2$. As the panels demonstrate, collective action in the **MUG** exhibits a very different behaviour as a function of group size in these 2 extreme cases: Whereas increasing group size allows for the evolution of societies in which Proposers offer smaller and smaller values of p (left panel) the opposite happens when unanimous acceptance is required. In both cases, however, one witnesses an increase of the q-value with increasing group size, although the increase is higher in the case $M=1$. Other parameters: $Z=1024$, $\mu=0.001$, $\varepsilon=0.05$ and $\beta=1$.

situations considered impart very different outcomes in what concerns the dependence of p on group size, as opposed to the dependence of q on group size, where we obtain, in both cases, a saturating increase with increasing group size, showing that larger groups tolerate, on average, more demanding *Responders*. In what concerns p, when a single *Responder* is enough to warrant a split ($M=1$), the left panel confirms the intuition that, the larger the group, the larger the probability that a single *Responder* will ratify the split, and hence p will evolve towards decreasing average values as a function of increasing group size N. On the other hand, whenever $M=N-1$, larger groups translate into stricter criteria of acceptance, given that unanimity among the *Responders* is now required. As a result, p becomes an increasing function of group size N in this case.

The two limiting cases studied above ($M=1$ and $M=N-1$) are but extreme cases of a richer portfolio of possibilities encompassed by the **MUG**. In Fig. 2 we show what happens for p as the value of M is gradually changed for 2 group sizes: $N=5$ (blue squares) and $N=15$ (red circles).

As expected (in view of the results of Fig. 1), one witnesses an increase of p with M for fixed group size; q, on the other hand, decreases with increasing M. This behaviour is more pronounced in large groups, where we witness a saturation of the changes in p and q for larger group sizes (see Fig. 1).

In order to shed light on the results we obtain numerically we discuss, in the following, the model introduced in Section 2.4, obtained by reducing the strategy space, and which allows us to discuss the evolutionary dynamics of the **MUG** analytically. Considering only 2 different values for both p and q, high (h) and low (l), we obtain 4 possible strategies (Gale et al., 1995; Nowak et al., 2000) of which we keep but 3: The *pro-Social* strategy $S=\{h,h\}$, the *Asocial* strategy $A=\{l,l\}$ and the *Generous* strategy. As stated in Section 2.4, we leave out the *Paradoxical* strategy $P=\{l,h\}$, as it always collects a payoff that is lower than any of the other three. While the *A*-strategy corresponds to the rational expectation in the 2-person **UG** (and also in the **MUG** – see Section 2 – given the limitations in the values of p and q), the *S*-strategy is closest to what is found to be employed by subjects of laboratory experiments in the **UG**.

In this subspace of three strategies, the evolutionary dynamics of a large population engaging in a **MUG** can be fully analyzed by computing the gradient of selection (Hofbauer and Sigmund, 1998; Pacheco et al., 2009) (see Section 2.4) in the full (triangular) simplex where all possible configurations of the population are represented. Each vertex of the simplex represents a monomorphic population, that is, populations in which all individuals adopt the same strategy. Edges of the simplex represent population configurations in which at least one of the strategies is missing. The interior of the simplex, in turn, corresponds to population configurations in which all strategies coexist, albeit with different fractions in different points. The analytical results for this simplified game, illustrated for the case in which $N=5$, $l=0.1$ and $h=0.6$, are shown in Fig. 3. Arrows represent the direction of selection within this space of configurations, while the color gradient illustrates the rate of evolution; empty (solid) circles denote unstable (stable) equilibria.

pro-Social and *Generous* are neutral with respect to each-other, something which is lost in the presence of *Asocial* individuals in the population. *Asocial* individuals engage in a *N*-person coordination game (Skyrms, 2004) with *pro-Social* individuals, while they strictly dominate *Generous* individuals. Hence, with increasing M (and fixed $N=5$), one observes a corresponding increase of the basin of attraction of the *Social* strategy that, in turn, leads to an increase of the overall area of the simplex in which the population evolves towards either *S*- or *G*-strategies. In light of these results, it is therefore easier to understand how the complex scenarios addressed in Figs. 1 and 2 emerge: By forcing that a proposal may be only accepted by a large number of responders, we are effectively enlarging the basin of attraction which leads to fairer offers (large p).

However, in this simplified setting, the evolutionary dynamics is purely deterministic. This, as is well known, is quite unrealistic, given the many sources of errors that one has identified to date in connection with the process of human decision making (Traulsen et al., 2010). The impact of stochastic effects has only been briefly considered within the context of Figs. 1 and 2.

In Fig. 4 we explicitly address the role played by both the selection pressure (β) and errors in perception (ε), showing that an overall increase of randomness – either by decreasing β or by increasing ε – increases the chance of fairer offers (higher p) and increasing demands (higher q), a result in line with (Rand et al., 2013) for the 2-person **UG**. Not only increasing noise will foster higher offers, stochastic effects of any kind, will act to disturb in a sizable way the evolutionary dynamics portrayed in Fig. 3, with the net effect that it will typically enable the population to circumvent the coordination barrier between S and A, driving the population towards S. Yet, as Fig. 4 also evidences, the conclusions regarding the role of M remain the same.

In summary, we have studied the evolutionary dynamics of the **MUG** – a **M**ulti-player version of the traditional 2-player **U**ltimatum **G**ame. We show that, when proposals are made to a group of individuals, evolution acts to select for low offers, the lower the smaller the number player(s) in a group required to ensure a successful split. This result can be understood intuitively in the
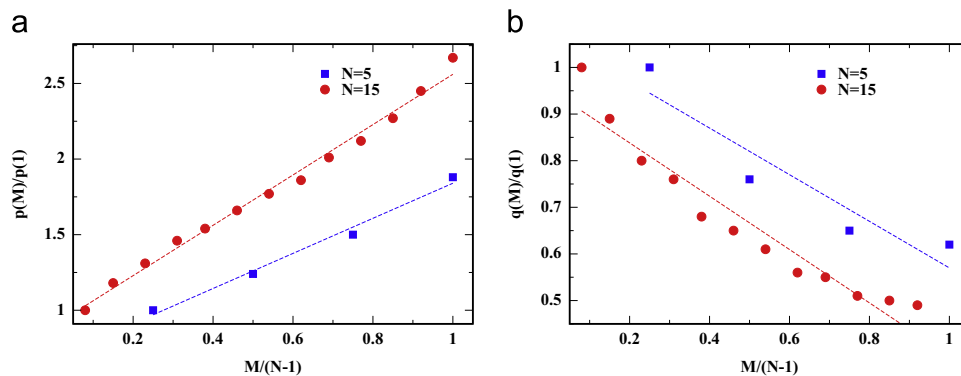

Fig. 2. Results for the (population wide) average values of p and q obtained as a result of computer simulations of the **MUG** in populations in which individuals start from a random distribution of strategies defined each by the duple $\{p,q\}$. We plot the values of p, panel (a), and q, panel (b), for different values of the ratio $M/(N-1)$, relative to the corresponding values for $M=1$ ($p=0.22$ and $q=0.25$ for $N=5$ and $M=1$, and $p=0.19$ and $q=0.42$ $N=15$ and $M=1$, respectively). In both panels, the dashed lines provide linear regression of the data, displayed to stress any non-linear behaviour of the values plotted. Other parameters: $Z=1024$, $\mu=0.001$, $\varepsilon=0.05$ and $\beta=1$. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)
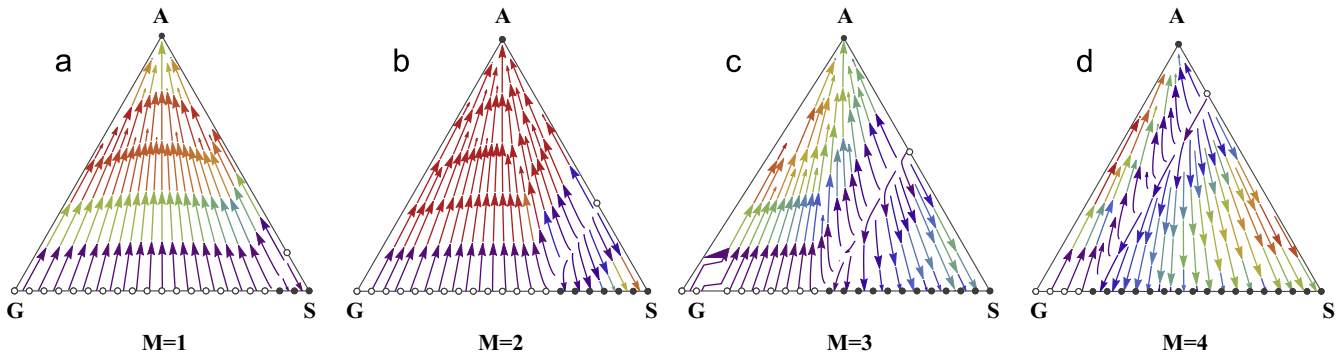
Fig. 3. Evolutionary dynamics involving the strategies *pro-Social* ($S,\{h,h\}$), *Asocial* ($A,\{l,l\}$) and *Generous* ($G,\{h,l\}$) for an infinite population in which both *Proposers* and *Responders* can only adopt low or high values. The dynamics is deterministic, in the absence of any type of errors. The Group size is $N=5$, whereas (without loss of generality) $l=0.1$ and $h=0.6$. From left to right we increase the minimum number M of *Responders* that are necessary to accept the *Proposer*'s offer (also shown the percentual fraction $M/(N-1)$ of *Responders* required for the Proposal to be accepted). With increasing M, one enlarges the region of the simplex in which *Asocial* players get extinct and *Generous* and *pro-Social* players co-exist. Note further that with increasing M, any source of noise (errors, trembling hand effects, etc.) may drive the population from a monomorphic *Asocial* configuration into a large basin of attraction where *pro-Social* and *Generous* players dominate, in agreement with the simulations described above (see also Fig. 4) where errors and other stochastic effects are explicitly considered. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article. We use a color scheme in which warmer colors are associated with higher speed of transitions.)
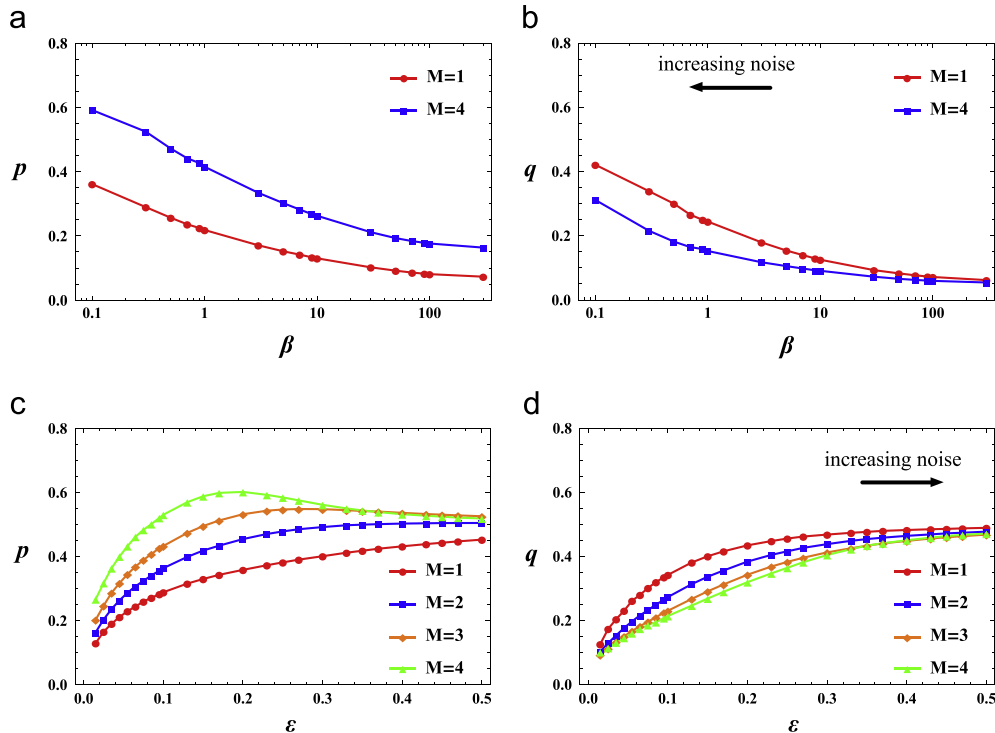

Fig. 4. Results for the (population wide) average values of *p* and *q in the stationary regime*, obtained as a result of computer simulations of the **MUG** ($N=5$) in populations in which individuals start from a random distribution of strategies defined each by the duple $\{p,q\}$. We plot the values of *p* (left, (a) and (c)) and *q* (right, (b) and (d)) for different values of the selection pressure (β, top, (a) and (b)), and perception errors (ε, bottom, (c) and (d)). Increasing the amount of noise, by either lowering β or increasing ε, leads to higher values of average *p* and *q*. The effects of stricter acceptance rules by the group are clearly maintained, regardless of the variations in β and/or ε: higher values of *M* result in higher values of average *p* and lower values of average *q*. Note finally, that there seems to be an ideal error rate at which fairness is maximized, and which is different from the optimal at ε which individuals become, on average, most demanding.

following way: If an individual knows that her proposal will have more than one responder, and if a single responder is enough to accept the proposal, the risk of having the proposal rejected is lower. Thus, she may try to maximize her gains, offering less. As the number of required acceptances increases, the probability to reach such consensuses decreases, and thus Proposers end up increasing *p* to compensate. This is fully confirmed by our results, which show that as the number *M* of individual Responders approaches the group size *N*, selection acts to increase the value proposed, leading to offers that compare more favorably with fair offers, although remaining always below the fair limit. As a result, *p* increases monotonously with *M*.

Our results, which match nicely those obtained experimentally, in the corresponding treatments, for $M=1$ and $M=N-1$ (Messick et al., 1997), extend our understanding of the dynamics of **MUG** to other regimes unexplored to date. They further highlight the subtle nature of *N*-person interactions, posing new challenges to our current understanding of the evolutionary routes of fairness. Indeed, most present and past human endeavors involve many individuals simultaneously (Dietz et al., 2003; Ostrom, 1990), instead of pairs of players ($N=2$). Yet, despite the complexity of the **MUG**, we address this problem in the absence of any additional mechanisms, such as community enforcement, reputations, norms or pledges (Binmore, 1998; Brandt et al., 2003; Nowak et al., 2000), peer punishment or

sanctioning institutions (Brandt et al., 2003; Fehr and Fischbacher, 2003; Sigmund et al., 2010). Needless to say, in real settings, groups will exhibit some form of context dependence and size heterogeneity that is well accounted by assuming the existence of an underlying network of interactions (Santos et al., 2008). The evolution of strategy adoption in the traditional 2-person **UG** was already addressed in models where individuals are arranged in lattices or networks (Iranzo et al., 2011; Killingback and Studer, 2001; Kuperman and Risau-Gusman, 2008; Page et al., 2000; Sinatra et al., 2009; Szolnoki et al., 2012a; Szolnoki et al., 2012b; Yang et al., 2015). Generally, this body of work shows that structure as well as noise (Chen et al., 2015; Page and Nowak, 2001; Page and Nowak, 2002; Page et al., 2000; Rand et al., 2013; Zhang, 2013) are able to promote fairness and empathy. It was also shown that, using different pairwise interaction paradigms, socially desirable strategies, as cooperation, are elicited by specific network topologies (Pinheiro et al., 2012; Santos et al., 2006). When these 2-person games are generalized to N-person situations (e.g. Public Goods Games), the impact of the underlying network of interaction may be different and should be studied in detail (Perc et al., 2013; Santos et al., 2008; Santos et al., 2012). The same may apply to **MUG** in the context of complex networks, especially since **MUG** cannot be built up by a set of independent pairwise **UG** encounters, even with the same opponents, given the existence of a group decision threshold (McAvoy and Hauert, 2015; Pacheco et al., 2009; Souza et al., 2009). Work along these lines will be needed to utterly appreciate the evolution of fairness in a multi-player context.

Irrespectively of the numerous extensions and layers of complexity which can be added, the present model already stresses that fair offers are fostered when an all-encompassing form of coordination is required – specially in large groups – a situation which, perhaps not by chance, is ubiquitous in Nature and the social dilemmas of collective action it portrays (Conradt and Roper, 2005; Conradt and List, 2009; Kao et al., 2014; Sumpter and Pratt, 2009). From nest-site selection and collective navigation to group hunting and the salvation of the planet against environmental hazards, examples abound where a large number of individuals must agree or reach a consensus before any significant outcome is produced, scenarios that, once more, cannot be described in the realm of 2-person interactions. Therefore, as has been argued for the two-player and multi-player Prisoner's Dilemma (Pacheco et al., 2009; Skyrms, 2004; Worden and Levin, 2007), by stressing the difficulty to achieve fair interactions on 2-player ultimatum games without recognizing that often we are dealing with more promising situations, may lead us to make over pessimistic predictions, and to overlook artless, yet important, routes to achieve cooperation.

References

Apicella, C.L., Marlowe, F.W., Fowler, J.H., Christakis, N.A., 2012. Social networks and cooperation in hunter-gatherers. Nature 481, 497–501. http://dx.doi.org/10.1038/nature10736.

Axelrod, R., Hamilton, W.D., 1981. The evolution of cooperation. Science 211, 1390–1396.

Barrett, S., 2003. Environment and Statecraft: The Strategy of Environmental Treaty-Making. OUP, Oxford.

Binmore, K.G., 1998. The evolution of fairness norms. Ration. Soc. 10, 275–301 http://dx.doi.org/10.1177/104346398010003001.

Bornstein, G., Yaniv, I., 1998. Individual and group behavior in the ultimatum game: are groups more "rational" players? Exp. Econ. 1, 101–108. http://dx.doi.org/10.1007/BF01426217.

Brandt, H., Hauert, C., Sigmund, K., 2003. Punishment and reputation in spatial public goods games. Proc. R. Soc. B 270, 1099–1104. http://dx.doi.org/10.1098/rspb.2003.2336.

Carman, K.G., 2003. Social Influences and the Private Provision of Public Goods: Evidence from Charitable Contributions in the Workplace. Manuscript, Stanford University.

Conradt, L., Roper, T.J., 2005. Consensus decision making in animals. Trends Ecol. Evol. 20, 449–456. http://dx.doi.org/10.1016/j.tree.2005.05.008.

Conradt, L., List, C., 2009. Group decisions in humans and animals: a survey. Philos. Trans. R. Soc. B 364, 719–742. http://dx.doi.org/10.1098/rstb.2008.0276.

Dietz, T., Ostrom, E., Stern, P.C., 2003. The struggle to govern the commons. Science 302, 1907–1912. http://dx.doi.org/10.1126/science.1091015.

Fehr, E., Schmidt, K.M., 1999. A theory of fairness, competition, and cooperation. Q. J. Econ. 114, 817–868. http://dx.doi.org/10.1162/003355399556151.

Fehr, E., Gächter, S., 2000. Fairness and retaliation: the economics of reciprocity. J. Econ. Perspect. 14, 159–181. http://dx.doi.org/10.1257/jep.14.3.159.

Fehr, E., Fischbacher, U., 2003. The nature of human altruism. Nature 425, 785–791. http://dx.doi.org/10.1038/nature02043.

Fehr, E., Schmidt, K.M., 2006. The economics of fairness, reciprocity and altruism-experimental evidence and new theories. In: Kolm, S. and Ythier, J.M. (Eds.): Handbook of the Economics of Giving, Altruism and Reciprocity, vol. 1, pp. 615–691.

Fischbacher, U., Fong, C.M., Fehr, E., 2009. Fairness, errors and the power of competition. J. Econ. Behav. Organ. 72, 527–545. http://dx.doi.org/10.1016/j.jebo.2009.05.021.

Fowler, J.H., Christakis, N.A., 2010. Cooperative behavior cascades in human social networks. Proc. Natl. Acad. Sci. USA 107, 5334–5338. http://dx.doi.org/10.1073/pnas.0913149107.

Gale, J., Binmore, K.G., Samuelson, L., 1995. Learning to be imperfect: the ultimatum game. Games Econ. Behav. 8, 56–90. http://dx.doi.org/10.1016/S0899-8256(05)80017-X.

Gintis, H., 2000. Strong reciprocity and human sociality. J. Theor. Biol. 206, 169–179. http://dx.doi.org/10.1006/jtbi.2000.2111.

Gintis, H., Bowles, S., Boyd, R., Fehr, E., 2003. Explaining altruistic behavior in humans. Evol. Hum. Behav. 24, 153–172. http://dx.doi.org/10.1016/S1090-5138(02)00157-5.

Gokhale, C.S., Traulsen, A., 2010. Evolutionary games in the multiverse. Proc. Natl. Acad. Sci. USA 107, 5500–5504. http://dx.doi.org/10.1073/pnas.0912214107.

Güth, W., Schmittberger, R., Schwarze, B., 1982. An experimental analysis of ultimatum bargaining. J. Econ. Behav. Organ. 3, 367–388. http://dx.doi.org/10.1016/0167-2681(82)90011-7.

Hardin, G., 1968. The tragedy of the commons. Science 162, 1243–1248.

Hauert, C., Michor, F., Nowak, M.A., Doebeli, M., 2006. Synergy and discounting of cooperation in social dilemmas. J. Theor. Biol. 239, 195–202. http://dx.doi.org/10.1016/j.jtbi.2005.08.040.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., 2004. Foundations of Human Sociality: Economic Experiments and Ethnographic Evidence from Fifteen Small-scale Societies. Oxford University Press, New York.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., McElreath, R., 2001. In search of homo economicus: behavioral experiments in 15 small-scale societies. Am. Econ. Rev., 73–78. http://dx.doi.org/10.1257/aer.91.2.73.

Henrich, J., Ensminger, J., McElreath, R., Barr, A., Barrett, C., Bolyanatz, A., Cardenas, J.C., Gurven, M., Gwako, E., Henrich, N., 2010. Markets, religion, community size, and the evolution of fairness and punishment. Science 327, 1480–1484 http://dx.doi.org/10.1126/science.1182238.

Hofbauer, J., Sigmund, K., 1998. Evolutionary Games and Population Dynamics. Cambridge University Press, UK.

Iranzo, J., Román, J., Sánchez, A., 2011. The spatial ultimatum game revisited. J. Theor. Biol. 278, 1-10, doi:10.1016/j.jtbi.2011.02.020.

Kao, A.B., Miller, N., Torney, C., Hartnett, A., Couzin, I.D., 2014. Collective learning and optimal consensus decisions in social animal groups. PLoS Comput. Biol. 10, e1003762. http://dx.doi.org/10.1371/journal.pcbi.1003762.

Killingback, T., Studer, E., 2001. Spatial ultimatum games, collaborations and the evolution of fairness. Proc. Royal. Soc. B 268, 1797-1801, doi:10.1098/rspb.2001.1697.

Kollock, P., 1998. Social dilemmas: the anatomy of cooperation. Annu. Rev. Sociol. 24, 183–214. http://dx.doi.org/10.1146/annurev.soc.24.1.183.

Kuperman, M., Risau-Gusman, S., 2008. The effect of the topology on the spatial ultimatum game. Eur. Phys. J. B 62, 233-238, doi:10.1140/epjb/e2008-00133-x.

Levin, S., 2012. The trouble of discounting tomorrow. Solutions 4, 20–24.

Maynard-Smith, J., Price, G., 1973. The logic of animal conflict. Nature 246, 15.

McAvoy, A., Hauert, C., 2015. Structure coefficients and strategy selection in multiplayer games. J. Math. Biol., 1-36, doi:10.1007/s00285-015-0882-3.

Messick, D.M., Moore, D.A., Bazerman, M.H., 1997. Ultimatum bargaining with a group: underestimating the importance of the decision rule. Organ. Behav. Hum. Decis. Process. 69, 87–101. http://dx.doi.org/10.1006/obhd.1997.2678.

Nowak, M.A., Sigmund, K., 2005. Evolution of indirect reciprocity. Nature 437, 1291–1298. http://dx.doi.org/10.1038/nature04131.

Nowak, M.A., Page, K.M., Sigmund, K., 2000. Fairness versus reason in the ultimatum game. Science 289, 1773–1775. http://dx.doi.org/10.1126/science.289.5485.1773.

Ohtsuki, H., Iwasa, Y., 2004. How should we define goodness?—reputation dynamics in indirect reciprocity. J. Theor. Biol. 231, 107–120. http://dx.doi.org/10.1016/j.jtbi.2004.10.001.

Ostrom, E., 1990. Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge University Press, New York.

Pacheco, J.M., Santos, F.C., Souza, M.O., Skyrms, B., 2009. Evolutionary dynamics of collective action in N-person stag hunt dilemmas. Proc. R. Soc. B 276, 315–321. http://dx.doi.org/10.1098/rspb.2008.1126.

Page, K. M., Nowak, M. A., Sigmund, K., 2000. The spatial ultimatum game. Proc. Royal. Soc. B 267, 2177-2182, doi:10.1098/rspb.2000.1266.

Page, K. M., Nowak, M. A., 2001. A generalized adaptive dynamics framework can describe the evolutionary Ultimatum Game. J. Theor. Biol. 209, 173-179, doi:10.1006/jtbi.2000.2251.

Page, K.M., Nowak, M.A., 2002. Empathy leads to fairness. Bull. Math. Biol. 64, 1101–1116. http://dx.doi.org/10.1006/bulm.2002.0321.

Perc, M., Gómez-Gardeñes, J., Szolnoki, A., Floría, L. M., Moreno, Y., 2013. Evolutionary dynamics of group interactions on structured populations: a review. J. R. Soc. Interface 10, 20120997, doi:10.1098/rsif.2012.0997.

Pinheiro, F. L., Pacheco, J. M., Santos, F. C., 2012. From local to global dilemmas in social networks. PLoS One 7, e32114, doi:10.1371/journal.pone.0032114.

Rabin, M., 1993. Incorporating fairness into game theory and economics. Am. Econ. Rev., 1281–1302.

Rand, D.G., Tarnita, C.E., Ohtsuki, H., Nowak, M.A., 2013. Evolution of fairness in the one-shot anonymous Ultimatum Game. Proc. Natl. Acad. Sci. USA 110, 2581–2586. http://dx.doi.org/10.1073/pnas.1214167110.

Rees, M.A., Kopke, J.E., Pelletier, R.P., Segev, D.L., Rutter, M.E., Fabrega, A.J., Rogers, J., Pankewycz, O.G., Hiller, J., Roth, A.E., 2009. A nonsimultaneous, extended, altruistic-donor chain. N. Engl. J. Med. 360, 1096–1101. http://dx.doi.org/10.1056/NEJMoa0803645.

Rendell, L., Boyd, R., Cownden, D., Enquist, M., Eriksson, K., Feldman, M.W., Fogarty, L., Ghirlanda, S., Lillicrap, T., Laland, K.N., 2010. Why copy others? Insights from the social learning strategies tournament. Science 328, 208–213. http://dx.doi.org/10.1126/science.1184719.

Robert, C., Carnevale, P.J., 1997. Group choice in ultimatum bargaining. Organ. Behav. Hum. Decis. Process. 72, 256–279. http://dx.doi.org/10.1006/obhd.1997.2738.

Sanfey, A.G., Rilling, J.K., Aronson, J.A., Nystrom, L.E., Cohen, J.D., 2003. The neural basis of economic decision-making in the ultimatum game. Science 300, 1755–1758. http://dx.doi.org/10.1126/science.1082976.

Santos, F. C., Pacheco, J. M., Lenaerts, T., 2006. Evolutionary dynamics of social dilemmas in structured heterogeneous populations. Proc. Natl. Acad. Sci. USA 103, 3490-3494, doi:10.1073/pnas.0508201103.

Santos, F.C., Pacheco, J.M., 2011. Risk of collective failure provides an escape from the tragedy of the commons. Proc. Natl. Acad. Sci. USA 108, 10421–10425 http://dx.doi.org/10.1073/pnas.1015648108.

Santos, F.C., Santos, M.D., Pacheco, J.M., 2008. Social diversity promotes the emergence of cooperation in public goods games. Nature 454, 213–216. http://dx.doi.org/10.1038/nature06940.

Santos, M.D., Pinheiro, F.L., Santos, F.C., Pacheco, J.M., 2012. Dynamics of N-person snowdrift games in structured populations. J. Theor. Biol. 315, 81-86, doi:10.1016/j.jtbi.2012.09.001.

Sigmund, K., 2010. The Calculus of Selfishness. Princeton University Press, Princeton, NJ.

Sigmund, K., De Silva, H., Traulsen, A., Hauert, C., 2010. Social learning promotes institutions for governing the commons. Nature 466, 861–863. http://dx.doi.org/10.1038/nature09203.

Sinatra, R., Iranzo, J., Gomez-Gardenes, J., Floria, L. M., Latora, V., Moreno, Y., 2009. The ultimatum game in complex networks. J. Stat. Mech. 2009, P09012, doi:10.1088/1742-5468/2009/09/P09012.

Skyrms, B., 2004. The Stag Hunt and the Evolution of Social Structure. Cambridge University Press, Cambridge.

Skyrms, B., 2010. Signals: Evolution, Learning & Information. Oxford University Press, Oxford.

Sumpter, D.J.T., Pratt, S.C., 2009. Quorum responses and consensus decision making. Philos Trans. R. Soc. B 364, 743–753. http://dx.doi.org/10.1098/rstb.2008.0204.

Szolnoki, A., Perc, M., Szabó, G., 2012a. Accuracy in strategy imitations promotes the evolution of fairness in the spatial ultimatum game. Europhys. Lett. 100, 28005, doi:10.1209/0295-5075/100/28005.

Szolnoki, A., Perc, M., Szabó, G., 2012b. Defense mechanisms of empathetic players in the spatial ultimatum game. Phys. Rev. Lett. 109, 078701, doi:10.1103/PhysRevLett.109.078701.

Tomasello, M., Call, J., 1997. Primate Cognition. Oxford University Press, Oxford.

Traulsen, A., Nowak, M.A., Pacheco, J.M., 2006. Stochastic dynamics of invasion and fixation. Phys. Rev. E 74, 011909. http://dx.doi.org/10.1103/PhysRevE.74.011909.

Traulsen, A., Semmann, D., Sommerfeld, R.D., Krambeck, H.-J., Milinski, M., 2010. Human strategy updating in evolutionary games. Proc. Natl. Acad. Sci. USA 107, 2962–2966. http://dx.doi.org/10.1073/pnas.0912515107.

Van Segbroeck, S., Pacheco, J.M., Lenaerts, T., Santos, F.C., 2012. Emergence of fairness in repeated group interactions. Phys. Rev. Lett. 108, 158104. http://dx.doi.org/10.1103/PhysRevLett.108.158104.

Vukov, J., Santos, F.C., Pacheco, J.M., 2011. Incipient cognition solves the spatial reciprocity conundrum of cooperation. PloS One 6, e17939. http://dx.doi.org/10.1371/journal.pone.0017939.

Worden, L., Levin, S.A., 2007. Evolutionary escape from the prisoner's dilemma. J. Theor. Biol. 245, 411–422. http://dx.doi.org/10.1016/j.jtbi.2006.10.011.