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A possible human counterpart of the principle of increasing entropy

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ABSTRACT

It is well-known that the principle of increasing entropy holds for isolated natural systems that contain non-adaptive molecules. Here we present, for the first time, an experimental evidence for a possible human counterpart of the principle in an isolated social system that involves adaptive humans. Our work shows that the human counterpart is valid even though interactions among humans in social systems are distinctly different from those among molecules in natural systems. Thus, it becomes possible to understand social systems from this natural principle, at least to some extent.

1. Introduction

Our world is composed of natural and social systems. From microscopic point of view, natural/social systems contain non-adaptive/adaptive molecules/humans that lack/own the adaptability to environmental changes because of the absence/presence of learning ability.

The principle of increasing entropy holds a supreme position among the laws of natural systems because all things in the observable natural systems are controlled by it. It may be expressed in the way that the thermodynamic entropy (s_t) of an isolated natural system should gradually increase until it reaches equilibrium with maximum thermodynamic entropy. It is well justified that the principle of increasing entropy holds for isolated natural systems that involve non-adaptive molecules. This is because molecules have higher probabilities to change from a regular motion to a thermal motion according to the theory of molecular motion. It was Boltzmann who bridged s_t and the thermodynamic probability (characterized by the number of microstates, Ω) as

$$s_t = k_B \ln \Omega, \tag{1}$$

where k_B denotes the Boltzmann constant.

Apparently, Eq. (1) is by no means valid only for natural systems with physical interactions among molecules because Ω can also be used to represent the number of microstates of social systems having interactions that differ from those among molecules. However, it is difficult to seek for the human counterpart in social systems. The challenge lies at least in two parts: (1) many social systems are open systems that exchange information with external environments, thus violating the conservation of energy required by the principle of increasing entropy; (2) social systems contain adaptive humans with many kinds of human behaviors, which implies that interactions among humans are quite different from those among molecules in natural systems. So far, to our knowledge, direct experimental evidences have never been shown for the human counterpart, despite of many attempts to apply thermodynamic laws in social systems [1–3]. Here we report one experimental evidence in a modeled isolated social system. The system of our interest involves human subjects competing for two resources with biased distributions which is a variant of the well known "El Farol Bar Problem" [4]. This system reflects some fundamental characteristics of real social systems [4–9], say, a balanced state emerged as a result of system efficiency [8,9]. The balanced state is just the equilibrium state with maximum entropy [9]. In the previous social systems [6,10], the concept of entropy which is represented from detailed historical information content indicates the relation between information and predictability, whereas in our system, the concept of entropy is quite different (we call it "entropy-like quantity"), which denotes the degree of uncertainty associated with macroscopic arbitrage opportunities. Accordingly, our results cannot be got from previous systems including minority game systems [6,10] as well as their superb extensions by other scholars [6,7,11]. To model the abundant human behaviors in real social systems, we take into account four kinds of behaviors, namely, normal behavior [5–8], herd behavior [12,9], contrarian

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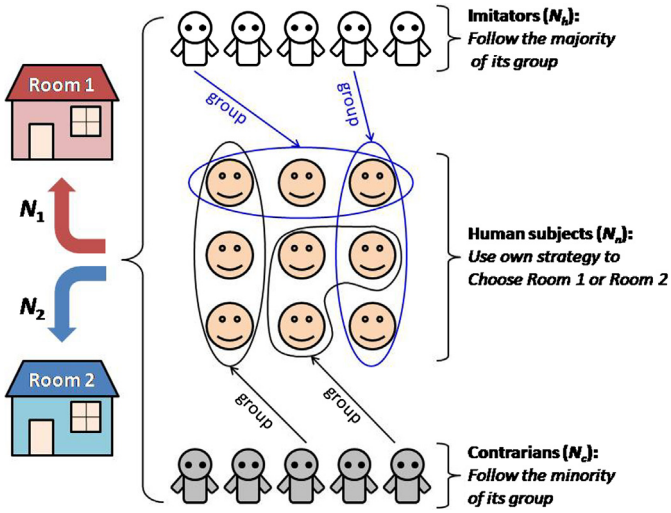

Fig. 1. (Color online.) Schematic diagram showing how imitators, human subjects, and contrarians choose to enter a room. More details can be found in the main text.

behavior [13–15], and hedge behavior. Let's proceed by introducing the human experiments.

2. Human experiments

The leaflet to the experiments is shown in Appendix A. We recruited 68 students and teachers from various departments of Fudan University as subjects. The experiment contains two virtual rooms, denoted as Room 1 and Room 2, with virtual amount of money, M_1 and M_2, respectively. The subjects do not know the values of M_1 and M_2 in every round of the experiment. Every human subject will choose to enter Room 1 or 2 independently in every round. The subjects entering Room 1 share the money M_1, and the subjects entering Room 2 share the money M_2. In the case where only the 68 human subjects existed, if the subjects in Room 1 obtain more per capita money than the subjects in Room 2, it is determined that the subjects who chose Room 1 win, and vice versa. Next, we extend this game to a complicated case. In order to include various kinds of human behaviors, the system may secretly add imitators and contrarians generated by the computer program which are not told to human subjects. In every round, each imitator and contrarian will randomly choose 5 human subjects as its group from 68 subjects, respectively. When all human subjects finished choices, then each imitator observed the choices of 5 human subjects in its group. If a imitator saw that the majority of its group chose to enter Room 1, then this imitator followed the majority to enter Room 1. If the majority of this imitator's group chose to enter Room 2, then this imitator followed the majority to enter Room 2. An inverse action will be performed by a contrarian. If the majority of a contrarian's group chose Room 1, then this contrarian followed the minority to enter Room 2, vice versa. In every round, the total number of subjects and imitators/contrarians who choose Room 1 (or Room 2) is denoted by N_1 (or N_2), respectively. Fig. 1 is the schematic diagram which shows the experiment process and agents' behavior. We remark the number of human subjects as N_n, the number of imitators as N_h, and the number of contrarians as N_c. We use β_1 (or β_2) to denote the ratio between the number of imitators (or contrarians) and subjects, that is, $\beta_1 = N_h/N_n$ (or $\beta_2 = N_c/N_n$). The total number of all the subjects, imitators, and contrarians is $N = N_1 + N_2 = N_n + N_h + N_c$. Because N_n is fixed throughout the experiments, we change N_c and N_h to adjust β_1 and β_2. In the experiment, $\beta_1 = 0$ and $\beta_2 = 0$ correspond to normal behavior, $\beta_1 \neq 0$ and $\beta_2 = 0$ represent herd behavior, $\beta_1 = 0$ and $\beta_2 \neq 0$ mean contrarian behavior, and $\beta_1 \neq 0$ and $\beta_2 \neq 0$ denote hedge behavior. All information including imitators (β_1) and contrarians (β_2) is not told to human subjects. At the end of each round, if $M_1/N_1 > M_2/N_2$, subjects in Room 1 win, and vice versa. Every subject can only be told his/her result (win or lose) after each round and make his/her own decision on choosing to enter which room for the next round. 30 rounds will be repeated under each parameter set of M_1/M_2, β_1 and β_2; see Appendix B. That is, this parameter set is kept constant for a given experimental run with 30 rounds. Besides an attendee fee, each subject will receive a salary which will be paid on the basis of the cumulative score he/she got in the experiments. Also, the top three subjects will be rewarded.

Clearly, the system (within a given experimental run with 30 rounds for the fixed set of M_1/M_2, β_1 and β_2) does not exchange information with external environments, and thus it can be seen as an isolated system. As a result, it is analogous to isolated natural systems which satisfy the conservation of energy.

3. Experimental results

To measure the degree of uncertainty associated with macroscopic arbitrage opportunities in our human system, we follow the definition of Shannon entropy [16] in information theory, and define the entropy-like quantity (s), a state function of our system, as

$$s = -(f_1 \ln f_1 + f_2 \ln f_2), \tag{2}$$

where $f_1 = \frac{\langle N_1\rangle/M_1}{\langle N_1\rangle/M_1 + \langle N_2\rangle/M_2}$ and $f_2 = 1 - f_1$. Here $\langle N_1\rangle$ (or $\langle N_2\rangle$) represents the round average of the numbers that the subjects choose to enter Room 1 (or Room 2). As a feature of our system with repeated actions, averaging for more rounds makes the resource allocation more efficient because of the increasing degree of human adaptability [8,9]. Thus, averaging over N_1 and N_2 for more rounds not only makes both $\langle N_1\rangle$ and $\langle N_2\rangle$ reflect the time passage of our repeated experiment (with total 30 rounds) for a fixed parameter set of M_1/M_2, β_1, and β_2, but also implies the system has a higher efficiency of resource allocation [8,9]. Accordingly, f_1 and f_2 denote the probabilities of two microstates (in a state of the system characterized by s) due to the existence of two rooms because $\langle N_1\rangle/M_1$ (or $\langle N_2\rangle/M_2$) represents the averaged number of subjects per amount of resources in Room 1 (or Room 2). It is worth noting that, when the number of rounds is large enough, $\langle N_1\rangle/M_1 = \langle N_2\rangle/M_2$ (or $f_1 = f_2 = 1/2$ herein) can appear as a special emergent result of the current system, e.g., for $M_1/M_2 = 3$ and $\beta_1 = \beta_2 = 0$ [8]. In this case, the whole system reaches equilibrium or balance and s has the maximum value of $s_{max} = 0.693$. Overall speaking, the state of the system with $s_{max} = 0.693$ corresponds to the fact that the macroscopic arbitrage opportunities are statistically exhausted in the whole system due to $\langle N_1\rangle/M_1 = \langle N_2\rangle/M_2$ [8,9]. Or, equivalently, the degree of uncertainty associated with the macroscopic arbitrage opportunities reaches maximum as $s_{max} = 0.693$. In addition, the first experimental round always tends to yield $N_1 = N_2$ (say, for $M_1/M_2 = 3$ and $\beta_1 = \beta_2 = 0$) because human adaptability has not started to play a role due to the lack of chances for learning. As a result, we have $\langle N_1\rangle/M_1 \neq \langle N_2\rangle/M_2$ or $f_1 \neq f_2$ when $M_1/M_2 > 1$. In this case, the macroscopic arbitrage opportunities are evidently the most, and the degree of uncertainty associated with them is the lowest accordingly. According to Eq. (2), its entropy-like quantity s is naturally smaller than 0.693 due to $f_1 \neq f_2$. Hence, we may conclude that the s defined in Eq. (2) describes the degree of uncertainty associated with macroscopic arbitrage opportunities as time elapses. Finally, to proceed, we add some more remarks on the definition of s. For a fixed parameter set of M_1/M_2, β_1 and β_2, the present system with 30 repeated experimental rounds

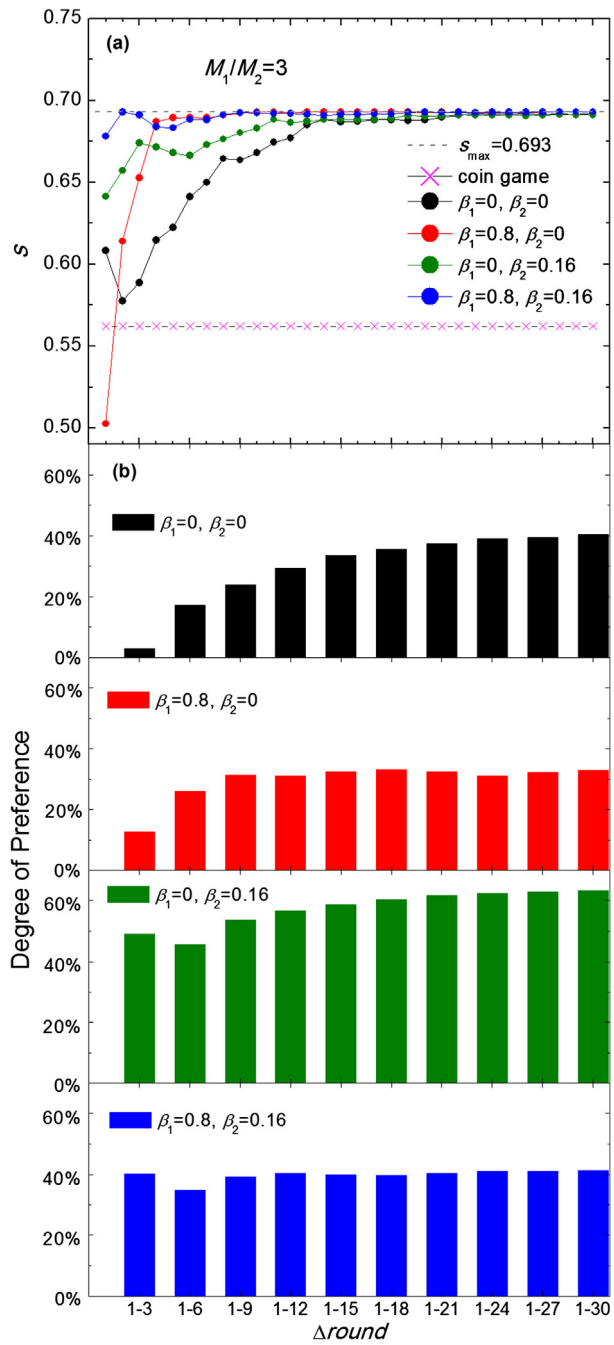

Fig. 2. (Color online.) Experimental results of (a) entropy-like quantity (s) and (b) DOP (degree of preferences) for $M_1/M_2 = 3$ with normal behavior ($\beta_1 = 0$ and $\beta_2 = 0$), herd behavior ($\beta_1 = 0.8$ and $\beta_2 = 0$), contrarian behavior ($\beta_1 = 0$ and $\beta_2 = 0.16$), and hedge behavior ($\beta_1 = 0.8$ and $\beta_2 = 0.16$), as a function of round intervals, Δround, which characterize the passage of time. For each parameter set (M_1/M_2, β_1 and β_2), human experiments with 68 subjects are repeatedly conducted for 30 rounds. The dashed line in (a) denotes the maximum value of entropy-like quantity, $s_{max} = 0.693$. The exact result of the coin game that has no human adaptability is also depicted in (a).

has 30 states, each characterized by the state function, s. The s of the jth ($j \leqslant 30$) state is calculated according to Eq. (2) by taking average over N_1 and N_2 from the first round to the jth round, thus named $s_{1\text{-}j}$. Fig. 2(a) shows experimental results for the time evolution of entropy-like quantity (s) from the 1st state ($s_{1\text{-}1}$) to the 30th state ($s_{1\text{-}30}$). We can see that for $M_1/M_2 = 3$, entropy-like quantity gradually increases to its maximum no matter what kinds of human behaviors are considered. However, one may argue whether this trend is generally true because it is only the result of

Fig. 3. Working panel for tossing a coin.

one repeated experiment (with 30 rounds). Frankly speaking, to make the results more solid, we should, in principle, follow either of the following two ways. (1) The first way is to let the same group perform the repeated experiment for P ($P \to \infty$) times, each yielding two values of N_1 and N_2 at the jth round. As a result, the desired value of entropy-like quantity, $s^{(1)}$, is calculated according to Eq. (2) where $\langle N_1 \rangle$ or $\langle N_2 \rangle$ should further be averaged over P times. (2) The second way is to let Q ($Q \to \infty$) groups conduct the repeated experiment separately, each also offering two values of N_1 and N_2 at the jth round. Similarly, the desired value of entropy-like quantity, $s^{(2)}$, is calculated according to Eq. (2) where $\langle N_1 \rangle$ or $\langle N_2 \rangle$ should further be averaged over Q groups. But, the two ways are practically impossible. The first way easily makes the subjects feel boring, thus causing data distortion, and the second way costs too much (say, human resources and money). Fortunately, we have an alternative method to show the generality of the increasing trend as already depicted in Fig. 2(a). Let us take the case of normal behavior ($\beta_1 = 0$ and $\beta_2 = 0$) as an example. At the first round of the repeated experiment, statistically speaking, subjects can only make decisions randomly, or, the probability for them to choose to enter Room 1 (Room 2) is 50% (50%) in spite of $M_1/M_2 = 3$. This is because these subjects have no information on how to choose or they have not yet got the chance to learn. In this case, human adaptability has not started to play a role in the value of $s_{1\text{-}1}$. After taking the above-mentioned averages over N_1's and N_2's for either P times or Q groups (if any), there must exist $s^{(1)}|_{1\text{st round}} = s^{(2)}|_{1\text{st round}} = 0.562$ according to Eq. (2) where $\langle N_1 \rangle / \langle N_2 \rangle = 1$ and $M_1/M_2 = 3$. On the other hand, if we consider the number of rounds is infinite, there is $s^{(1)}|_\infty = s^{(2)}|_\infty = 0.693 \equiv s_{max}$ according to Eq. (2) where $\langle N_1 \rangle / \langle N_2 \rangle = M_1/M_2 = 3$ due to the full role of human adaptability [8]. In other words, the single curve for $\beta_1 = \beta_2 = 0$ in Fig. 2(a) stands for one realistic trajectory from $s^{(1)}|_{1\text{st round}} = s^{(2)}|_{1\text{st round}} = 0.562$ to $s^{(1)}|_\infty = s^{(2)}|_\infty = 0.693$. This trajectory overall increases, as we expected. The arguments hold the same for the other three cases (herd behavior, contrarian behavior, and hedge behavior) as shown in Fig. 2(a). Thus, we may conclude that the increasing trend displayed in Fig. 2(a) is general. To further understand its mechanism, we suggest to carry a coin game as a non-adaptive counterpart to compare with human experiments. For this purpose, we design a coin game program (Fig. 3) in which all the subjects are imagined to make decisions according to tossing a coin. The "50%" on the toss panel shown in Fig. 3 means that either the head (H) or the tail (T) of the coin has the probability of 50% to appear, after clicking the button "Click Here to Flip the Coin" and then the button "Stop" on the panel. If "H" (or "T") means requesting a subject to choose to enter Room 1 (or Room 2), the model

series of "HHHTHTTHHTTTHT" as a result of 14 rounds shown on the panel let the subject choose to enter Room 1 or Room 2 accordingly. Because the coin game has no human adaptability at all, the probability for the head (or tail) of the coin to appear is set to be 50% in view of the existence of two rooms in our human experiment. As a result, each subject has the probability of 50% to enter Room 1 or Room 2 although $M_1/M_2 = 3$ and four different kinds of human behaviors have been adopted in our experiment. Eventually there must be $s^{(1)}|_{1\text{st round}} = s^{(2)}|_{1\text{st round}} = s^{(1)}|_\infty = s^{(2)}|_\infty = 0.562$ for the coin game, due to $\langle N_1\rangle/\langle N_2\rangle = 1$ and $M_1/M_2 = 3$. The entropy-like quantity corresponding to the coin game has been shown in Fig. 2(a). So far, it becomes convinced that the trend of entropy-like quantity s for different behaviors (Fig. 2(a)) generally increases as time evolves, which originates from the role of human adaptability. This increasing trend evidently echoes with the statement of the principle of increasing entropy. Nevertheless, we also observe that the increasing trend of s in Fig. 2(a) is not always monotonic. This can be qualitatively understood in view of the fluctuation theorem [17]. The theorem [17] conveys the fact that thermodynamic entropy has a probability to flow in a direction opposite to that dictated by the principle of increasing entropy. This theorem may also have a human counterpart in our system, as implied by Fig. 2(a).

So far, we have investigated the case of a biased distribution of resources ($M_1/M_2 = 3$). In fact, we can also study the unbiased distribution of resources ($M_1/M_2 = 1$) on the same footing, which is exactly the original minority game system [5,6]. Nevertheless, it can be readily concluded that this case ($M_1/M_2 = 1$) also yields $s^{(1)}|_{1\text{st round}} = s^{(2)}|_{1\text{st round}} = s^{(1)}|_\infty = s^{(2)}|_\infty = 0.693 \equiv s_{max}$ for normal behavior. This is because, for $M_1/M_2 = 1$, the subjects choose to enter Room 1 (or Room 2) with probability 50%. In this case, the entropy-like quantity keeps not only unchanged but also maximum (s_{max}) as time evolves. Similar conclusions also work for the other three cases (herd behavior, contrarian behavior, and hedge behavior). In other words, the original minority game system has no human counterpart of the principle of increasing entropy.

The above analysis has qualitatively shown the influence of human adaptability. But, to quantitatively understand the presence of human adaptability, we need to define another quantity, namely, the average degree of preferences (DOP), $\text{DOP} = |1 - 2\rho| \times 100\%$, where ρ denotes the mean preference of all the 68 subjects. Note the preference of an individual subject is defined as the ratio between the number of choosing to enter Room 1 and that of experimental rounds [9]. Thus, the DOP means whether the subjects have preferences to choose to enter one of the two rooms. For example, DOP = 0% means the subjects have no preference to a certain room, or their chance to choose Room 1 equals that to choose Room 2. DOP = 100% means the subjects completely prefer one of the two rooms. Fig. 2(b) shows two evidences for the presence of human adaptability. One is that the DOP has quite different frameworks as different behaviors are adopted. The other is that, for a specific behavior, the DOP changes as time evolves. The two evidences just result from the evolution of heterogeneous preferences of individual subjects according to the definition of DOP.

4. Agent-based modeling and simulation results

The above experimental evidence for the human counterpart of the principle of increasing entropy is robust to four kinds of human behaviors. However, these experiments were conducted for specific population (students and teachers from Fudan University) at particular time and avenue (a computer room). To extend the experimental results beyond such restrictions, we establish an agent-based model [4–9,18–20], so that we are allowed to understand the experimental social system from agent-based modeling in a more general sense, at least to some extent. In this model, there are N_n normal agents, N_h imitators, and N_c contrarians. Here, normal agents correspond to subjects in the human experiments and each of them chooses to enter one of the two rooms using their own strategy table; see Fig. 4. The strategy table is constructed by two columns as shown in Fig. 4. The left column represents λ potential situations and the right column is filled with 0 and 1 according to an integer, L. Here 1 and 0 represent choosing to enter Room 1 and Room 2, respectively. Each strategy table is with a certain value of L, which characterizes the heterogeneity in the decision-making process of normal agents. For a certain value of $L(L \in [0, \lambda])$, there is a probability of L/λ to be 1 in the right column of the table and a probability of $(\lambda - L)/\lambda$ to be 0. At each time step, normal agents choose to enter a room according to the right column of the strategy tables under the given situation λ_i, $\lambda_i \in [1, \lambda]$. Before the simulation starts, every normal agent will randomly choose Ω strategy tables. At the end of every time step, each normal agent will score the Ω strategy tables, respectively. Then, the strategy table ranked as the best (namely, with the highest score) will be used for the next time step. Additionally, imitators and contrarians have no strategy tables, whose decisions are based on the choices of normal agents according to the same rules provided in the section of Human Experiments.

Now we are in a position to analyze entropy-like quantity (s) and DOP on the basis of the simulation data; see Fig. 5. Fig. 5(a,b) shows simulation results for $M_1/M_2 = 3$. Evidently, the entropy-like quantity also gradually increases up to its maximum no matter what kinds of behaviors are taken into consideration (Fig. 5(a)), which echoes with Fig. 2(a). Meanwhile, the DOP in Fig. 5(b) also varies accordingly, and has a framework similar to that in Fig. 2(b). Thus, Fig. 5(a, b) not only confirms the above experimental findings, but also extends them to a more general case being beyond the experimental restrictions on specific subjects, time and avenue. Moreover, besides $M_1/M_2 = 3$ in Fig. 5(a, b), Fig. 5(c–f) also shows the simulation results for $M_1/M_2 = 2$ and $M_1/M_2 = 4$, in order to extend the case of a specific biased distribution of resources ($M_1/M_2 = 3$) to more relevant systems. According to the analysis in the previous section, for $M_1/M_2 = 2$ (or $M_1/M_2 = 4$), we have $s^{(1)}|_{1\text{st round}} = s^{(2)}|_{1\text{st round}} = 0.637$ (or 0.500) and $s^{(1)}|_\infty = s^{(2)}|_\infty = 0.693 \equiv s_{max}$. All the results obtained from Fig. 2(a, b) and Fig. 5(a, b) qualitatively hold for Fig. 5(c–f) as expected.

5. Discussion and conclusions

We have presented the first direct experimental evidence for the human counterpart of the principle of increasing entropy in a modeled isolated social system. The results obtained from agent-based simulations have further confirmed it in a more general sense. Even though such a human counterpart cannot exist in the original minority game system (which have an unbiased distribution of two resources [5,6]), besides the present system with a biased distribution of two resources, the human counterpart might also appear in some other social systems where repeated decisions are needed, for example, iterated prisoners' dilemma [21] and sequential bargaining [22].

Our work shows that this human counterpart holds even though interactions among humans in social systems (arising from human adaptability) distinctly differ from those among molecules in natural systems. In our systems, the interactions of the adaptive agents make agents flock to the direction without arbitrage opportunity where the system achieves finally equilibrium. Entropy-like quantity reaches its maximum when the arbitrage opportunities of the two rooms are equivalent. Meanwhile, the player cannot increase own score by changing own choice. However, when the entropy-like quantity does not yet reach its maximum value, there is always one room whose arbitrage opportunity is higher than the other. Thus, the players may choose the room with a higher

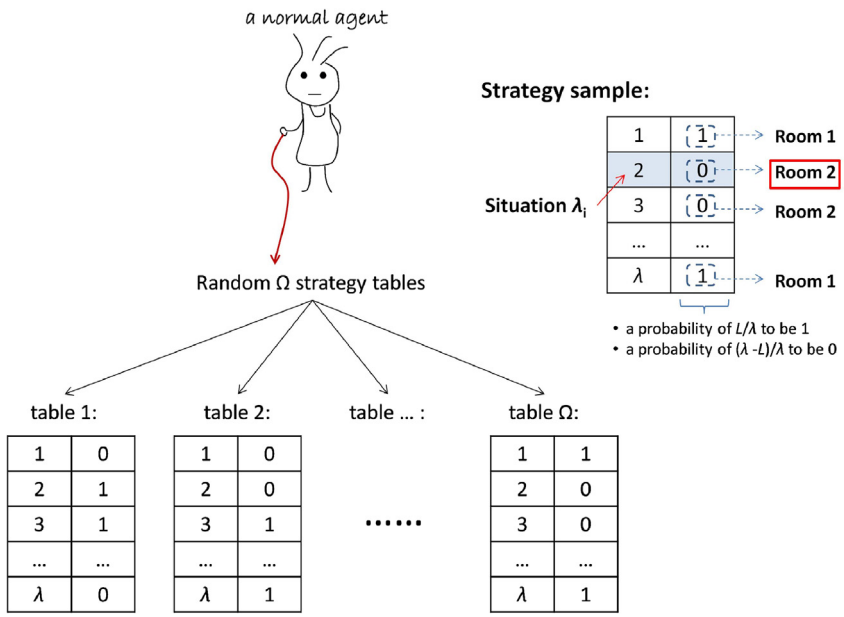

Fig. 4. (Color online.) Schematic graph showing strategy tables of a normal agent. Each normal agent is allocated Ω strategy tables. After scored at the end of every simulating round, the best strategy is used for the next round. In the strategy sample, the current situation is $\lambda_i = 2$, whose right column is 0, and thus this agent will choose to enter Room 2 in this round.

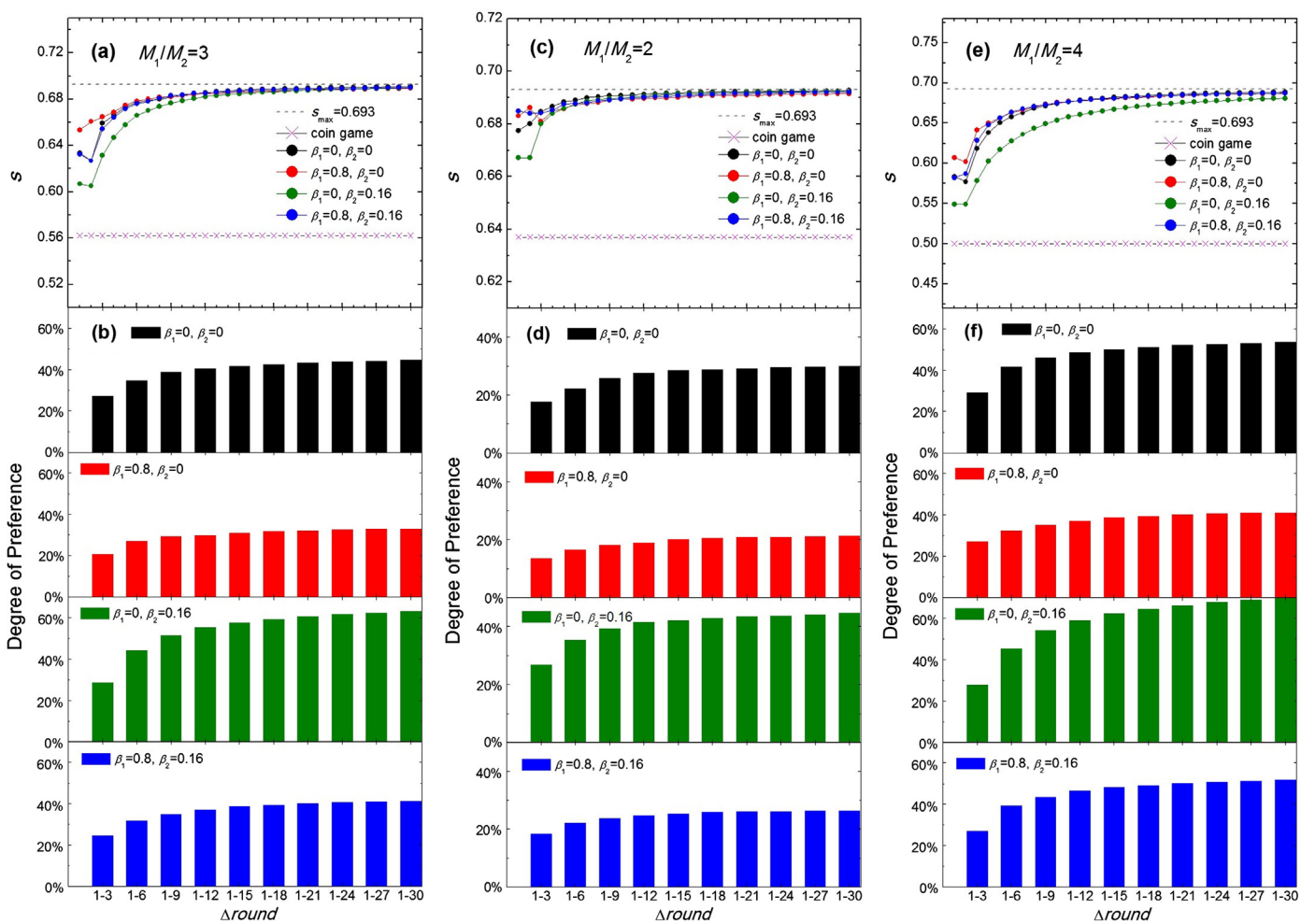

Fig. 5. (Color online.) Same as Fig. 2, but for results obtained from the agent-based simulations. Besides $M_1/M_2 = 3$, $M_1/M_2 = 2$ and $M_1/M_2 = 4$ are also shown. For each parameter set (M_1/M_2, β_1 and β_2), simulations with 68 normal agents are also run for 30 time steps, in order to echo with human experiments (68 subjects and 30 rounds). Parameters: $\Omega = 10$ and $\lambda = 100$. Both the maximum entropy-like quantity line ($s_{max} = 0.693$) and the coin game result are also depicted in (a), (c) and (e).

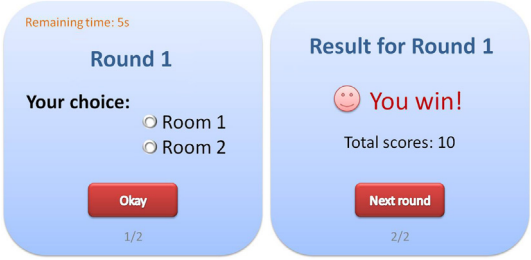

Fig. 6. (Color online.) Working panel for each subject.

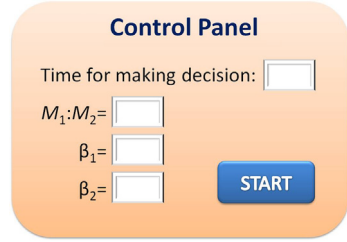

Fig. 7. (Color online.) Control panel for the experimental organizer.

arbitrage opportunity to obtain a higher score. Because the winning rule is $M_1/N_1 > M_2/N_2$, the player choosing the room with a higher arbitrage opportunity will inevitably result in the reduction of the winning rate of this room. Our results show that the arbitrage opportunities of the two rooms eventually return to equivalence at the end of each experiment. That is, there is no arbitrage opportunity in the whole system. It illustrates that in our systems the principle of increasing entropy-like quantity can describe the evolution of macroscopic quantity, N_1/N_2. Thus, it becomes possible to provide some new insights into some social systems from this principle originating from natural systems, at least to some extent. For example, in economics/finance, this work implies that, when the "invisible hand" tends to play a full role in a free (isolated) market, the dynamic process is accompanied with the increase of the degree of uncertainty associated with macroscopic arbitrage opportunities.

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Appendix A. Leaflet to the experiment

Welcome! Please read this leaflet carefully. Once the experiment starts, any kind of communication is forbidden.

Everyone completes this experiment via a computer in front of you. You will use an allocated anonymous account throughout the experiment. After logging in, you will see two virtual rooms in Page 1/2 (Fig. 6): Room 1 and Room 2. Each room owns a certain amount of virtual money, labeled as M_1 and M_2, but you are not told the amount and ratio, M_1/M_2. You can choose to enter one of the two rooms, and then click "Okay" and wait. Those who chose to enter the same room will share alike the virtual money inside it. After all the subjects finish, the system will calculate per capita money of the two rooms, respectively. The room in which subjects get higher per capita money is regarded as the winning room and the subjects who had chosen to enter the winning room as winners in this round. Then Page 1/2 will automatically turn to Page 2/2 (Fig. 6). You will see the result of this round and the current score. After that, Page 2/2 will automatically turn back to Page 1/2 and next round starts. Each parameter set lasts 30 rounds. For all the experiments, the total number of human subjects was kept at 68, but the number of subjects entering Room 1 and Room 2 in every round will not be announced. Each subject cannot see the other subjects' options. Only your own result will be told after every round, as shown by Page 2/2. You can only use this information to judge which room to choose to enter in the next round.

Each account has an original score with 0 point. 10 points will be added in every round if you win and 0 point will be added if you lose. After completing all the experimental rounds, you will receive a salary which will be paid on the basis of your cumulative score according to the exchange rate: 10 points = 1 Chinese Yuan. Besides, we will reward the top three subjects with additional 100 Chinese Yuan. In addition, every subject will receive 30 Chinese Yuan as an attendee fee. Try to win more money!

Appendix B. Control panel for the experimental organizer

In order to conduct the experiment of Appendix A, the experimental organizer has a control panel; see Fig. 7. According to the panel, it is evident that for one repeated experiment (30 rounds), we fix the parameter set of M_1/M_2, β_1, and β_2. Incidentally, the panel is not shown to the subjects during the experiments, so that all the subjects could not know any values of M_1/M_2, β_1, and β.

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