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# Reciprocity in Repeated Emotion Game Experiments: Analyses of a Game-Theoretic Econometric Model

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## Abstract

We conducted three treatments of human-computer repeated emotion game experiments and set up a game-theoretic econometric model to measure the impact of emotional reciprocity on behavior at the group level when self-interest is impossible. We found that the subjects still gave feedback in response to the opponent's friendliness (unfriendliness), even if their behaviors could not change their expected payoffs. The subjects' willingness to be altruistic increased in the level of altruism in the environment. However, when the opponent did not respond to their behaviors, the subjects' willingness to be altruistic was lower than their opponents, especially when the opponents behaved more altruistically.

## Keywords

Reciprocity, Emotion Game, Experiment, Game-Theoretic Econometric Model

## 1. Introduction

A large number of studies show that when people make economic decisions, they not only pay attention to their own payoffs but also to those of others, thus generating social emotions such as altruism (Charness & Rabin, 2002), spitefulness (Fehr, Hoff, & Kshetramade, 2008), inequality aversion (Blanco, Engelmann, & Normann, 2011) and reciprocity (Hein, Morishima, Leiberg, Sul, & Fehr, 2016). Models that include payoff and emotional utility are more accurate in describing individual utility than those only considering self-interest; however, doing so also makes distinguishing the influence of emotion and own payoff on behavior more difficult in most cases because changes in individual behaviors

often lead to simultaneous changes in individual payoffs and emotional utility, and the subject has to trade off between self-interest and emotion (Fehr & Camerer, 2007).

Reciprocity refers to that people will provide feedback to people who are (un)friendly to them. Reciprocity is often associated with improving one's expected payoffs. For example, in the repeated prisoner's dilemma, the tit-for-tat strategy is a typical reciprocity strategy, which is often used to stimulate cooperation (Becker, 1974) to achieve self-interest. Then, when self-interest cannot be realized, how much emotional feedback will people give in response to opponent's (un)friendliness? In this study, we attempt to exclude the influence of self-interest (changes in one's own payoff) on behavior and only measure the subjects' emotional reciprocity aroused by how others treat them. We conducted three treatments (with different altruistic environments) of human-computer repeated emotion game experiments and set up a game-econometric model to estimate the altruism coefficient at the group level in each treatment, revealing the subjects' willingness to be altruistic in different altruistic environments. We found that the more altruistic an environment was, the higher the willingness of the subjects to be altruistic. These results reflect the subjects' pure emotional feedback to the environment, which explains why an altruistic environment is conducive to the emergence of altruistic behavior.

## 2. Emotion Game and Method

The important feature of the emotion game is that it can separate the influences of payoffs and emotions on behavior. The payoff matrix of the emotion game is as follows:

|  | | player 2 | |
|---|---|---|---|
|  | | 1 | 2 |
| player 1 | 1 | 1, 1 | 2, 1 |
|  | 2 | 1, 2 | 2, 2 |

In the emotion game, player 1's action does not affect his/her payoff but can completely determine player 2's payoff, just as in generosity game (Güth, 2010), the proposer does not have to trade off between one's own payoff and responder's payoff. When player 1 chooses option 2, he/she can generate more payoffs for player 2 at no material cost, which is costless altruistic behavior. In a one-shot emotion game, if player 1 only focuses on his/her own payoff, then the two options are neither good nor bad, he/she can choose randomly. The payoff matrix is symmetrical, and the same is true for player 2. Therefore, there are infinite Nash equilibria. For player 1 (2), at the group level, each of the two actions appears with an equal probability of 0.5 (Fehr, Bernhard, & Rockenbach, 2008). Similarly, in repeated emotion games, if player 2 chooses randomly according to a fixed probability, which means that player 2 does not respond to player 1's be-

haviors, player 1's expected payoff is also fixed. If player 1 only cares about his/her own payoff, he/she still randomly selects between the two options. For a population of player 1s, each of the two actions still appears with equal probability 0.5.

However, if player 1 cares about his/her own and his/her opponent's payoff, then his/her utility function will include emotional utility. The emotional utilities under different combinations of actions by both players are unequal, and player 1 will no longer choose randomly. When we only consider the emotions related to the results of the two players' payoffs, if player 1 is purely altruistic, he/she does not pay attention to another player's action, his/her utility will increase as long as the opponent's payoff increases (Charness & Rabin, 2002), so he/she would always choose the altruistic option 2. In contrast, if player 1 is spiteful (Charness & Rabin, 2002), he/she always chooses option 1. If player 1 cares about the equality of payoffs, any payoff difference between the two players will reduce his/her utility (Charness & Rabin, 2002), and he/she attempts to make his/her behaviors consistent with player 2's behaviors. As mentioned above, his/her payoff does not depend on his/her own behavior, and he/she does not need to be self-interested under the condition that the opponent choosing randomly according to a fixed probability in repeated emotion games. Therefore, if the frequency with which a population of player 1's choosing option 2 deviates significantly from 0.5, this can be explained by emotional factors. It is feasible to study the only influence of emotion on behavior in repeated emotion games.

Reciprocity means that people are friendly to others who are friendly to them and unfriendly to those who are not. Reciprocity is a dynamic process, which doesn't have to happen in repetitive interactions, and which is also at work when there is only a single round of interaction. Trust is often considered to be related to reciprocity. Conducting a one-shot trust game with two-way anonymity (Berg, Dickaut, & McCabe, 1995) can reveal the pure trust level. The amount invested by the principal is used to measure the trust level, and the share of the rewards returned to the agent is used to measure the extent to which the agent is trusted. However, reciprocity is related to the perception of others' intentions, and a single interaction is insufficient to measure it, repetitive interactions are conducive to the player understanding the opponent's intentions better. And in those games (e.g. trust game, prisoner's dilemma, and gift exchange game, etc) which are used to study reciprocity, individual behavior always affects one's own payoff, and behaviors reveal more than people's emotional reciprocity. In the repeated emotion game where one player chooses randomly according to a fixed probability, it is feasible to consider only the emotional reciprocity in repeated interaction. The fixed probability actually represents the opponent's intention of how he/she treats the player. The higher the probability is, the friendlier the opponent is, and the more altruistic the environment is. By using the behaviors of the subjects in different altruistic environments to estimate the willingness of the

subjects to be altruistic, we can measure how people respond to others' friendliness and unfriendliness—the degree of emotional reciprocity. Different individuals may have different emotional responses in the same situation. We do not emphasize individuals but instead focus on the characteristics of the group and measure reciprocity at the group level.

We can establish a game-theoretic model to explore what emotions and how emotions affect player 1 s' behaviors using behavioral data for the subjects of the experiment. A game-theoretic econometric model (Kooreman, 1994) combines game theory with econometrics and does not solve for the equilibrium of the game under the assumption that the players' payoff functions are known, as would be the case in standard game theory. In a game-theoretic econometric model, given the number of players in the game and the optimal strategies, it is assumed that the forms of the players' utility functions (under the combination of the strategies of all players) are known, and an equilibrium of the game equilibrium exists, with the observed results being considered the equilibrium. By introducing random error into the players' utility functions, according to the conditions of the error when the equilibrium occurs, maximum likelihood estimation or other methods are used to estimate the unknown parameters of the utility function or response function based on the observed behavioral data to find out the influence factors of behaviors and forecast. A game-theoretic econometric model provides a way to measure social emotion under the condition of strategic interaction. In some studies of measuring emotional utility, strategic interaction only appears in the decision-making situation, the possible emotion utilities are included in the individual utility function of one player (Charness & Rabin, 2002; Charness & Haruvy, 2002), and the relevant emotion utility coefficient is estimated according to the experimental data by using the maximum likelihood estimation. For example, in gift exchange game experiments, the researchers based on the behavioral datum of employees estimated altruism, inequality aversion coefficients and the weight of reciprocity in the utility function at the group level (Charness & Haruvy, 2002). Similarly, we can also write the emotional utility related to the results of both players into the individual utility function, however, establish a game-theoretic econometric model to estimate the relevant emotional utility coefficients according to the conditions of Nash equilibrium (strategic interaction of both players).

## 3. Experimental Design

Our repeated emotion game experiments included three treatments: a weak altruistic emotion game (WAEG), a middle altruistic emotion game (MAEG) and a strong altruistic emotion game (SAEG); in these games, the computer chose the altruistic action 2 with probability $q$ of 1/3, 1/2, and 2/3, respectively. We use the computer as the human player's opponent to choose randomly following a fixed probability. Game experiments often use virtual computer players (Brenner & Vriend, 2006; Mccabe, Houser, Ryan, Smith, & Trouard, 2001; Winter & Za-

mir, 2005; Houser & Kurzban, 2002; Ferraro, Rondeau, & Poe, 2003; Yamakawa, Okano, & Saijo, 2016; Cox, 2017), which are easy to control. This is a feasible approach because although people may be less altruistic when interacting with the computer than when interacting with a human opponent, the subjects' feedback on how the opponent treats them will not be reduced (Sandoval, Brandstetter, Obaid, & Bartneck, 2016). What we are really interested in is how people respond to the way in which their opponents treat them.

Each subject played 100 rounds of repeated emotion games with his/her computer opponent (partner). The subjects knew the total number of rounds and that his/her computer opponent randomly selected following a fixed probability, but they did not know the value of the probability $q$. The computerized experiments were programmed in Z-Tree software (Fischbacher, 2007). The human player and his/her computer opponent made decisions at the same time. At the end of each round, the computer fed back the choices, the nominal payoffs and the accumulated nominal payoffs of the two players in the current round. Ninety-six subjects participated in the experiment in each treatment, for a total of 288 subjects. The experiments were conducted at Beijing Normal University in June and September 2016. The subjects were recruited by the BBS (Bulletin Board System) of Beijing Normal University. They came to the laboratory at a specified time. After the introduction of the experiment, the experiment began. At the end of 100 rounds, the subject's 100 rounds of accumulated nominal payoffs were converted into a real payoff at a rate of 5 nominal payoffs = 1 CNY (Chinese currency). The subjects confirmed and then completed a personal information questionnaire (see Appendix Table A1 for demographic statistics). The total payoff of the experiment was the real payoff plus the questionnaire reward of 10 CNY. The average payoff of the 288 subjects was 40 CNY (5.65 USD). The experiment lasted approximately 40 minutes.

## 4. Model

In our game-theoretic econometric model, each of the two players can take one of two actions. The action that player $i, (i = 1, 2)$ takes is $a_i \in A_i$, $A_i = \{1, 2\}$. The utility of player $i$ obtained from each of the four possible action combinations is denoted by $U_i(a_1, a_2)$. In the experiments, the computer player (player 2) chooses action 2 with a given probability, and it had no obligation to maximize its utility. Therefore, we only define the human player's (player 1) utility $U_1(a_1, a_2)$ as follows:

$$
\begin{aligned}
U_1(a_1, a_2) &= U(a_1, a_2) \\
&= \pi_1(a_1, a_2) + \phi \pi_{-1}(a_1, a_2) + \lambda \left| \pi_1(a_1, a_2) - \pi_{-1}(a_1, a_2) \right| + \varepsilon_{1s}.
\end{aligned} \tag{1}
$$

In Equation (1), $\pi_1(a_1, a_2)$ $(\pi_{-1}(a_1, a_2))$ is the human player's (computer player's) nominal payoff derived from the combination of actions $(a_1, a_2)$. $\phi \pi_{-1}(a_1, a_2)$ is the human player's emotional utility derived from action $a_1$, which makes his/her computer opponent's payoff $\pi_{-1}(a_1, a_2)$. $\phi$ is the altru-

ism coefficient, where $\phi > 0$ is altruistic and $\phi < 0$ is not altruistic (or spiteful). $\lambda|\pi_1(a_1,a_2) - \pi_{-1}(a_1,a_2)|$ represents the human player's aversion to payoff inequality. $\lambda(\lambda \leq 0)$ is the inequality aversion coefficient, that is, the reduction in emotional utility caused by the difference in the unit payoff. $\varepsilon_{1s}$ is the random error of the human player choosing actions $s,(s = 1, 2)$, and $\varepsilon_{11}, \varepsilon_{12}$ are continuous random variables that are independent of one another.

Altruism, inequality aversion and spitefulness, which are all related to payoff results, are included in the model. Furthermore, we can discuss reciprocity by comparing the altruism coefficients in different altruistic environments. When the altruism coefficient $\phi > 0$ ($\phi < 0$), the greater (smaller) $\phi$ is, the more emotional utility was increased (decreased) by increasing the opponent's unit payoff. Therefore, the altruism coefficient represents the willingness of the human players to be altruistic. If there are significant differences among the altruism coefficients in the three environments, it illustrates that the environment's degree of altruism affects behaviors of the human players, and the human players have unilateral emotional reciprocity to the environment. If differences exist, then they should appear after the human players understand the environment (the computer's intention), not in the first round. Therefore, we can examine whether there are differences in the human players' actions in the first round; if there are no differences, the human players can be considered to be randomly sampled from the same population. Furthermore, if there are differences among the human players' actions in the last 10 rounds in different environments, then we can comparatively study the human players' willingness to be reciprocal.

To solve the model, the human player's utility under the four kinds of action combinations is as follows:

$$\begin{aligned}
U(2,2) &= 2 + 2\phi + \varepsilon_{12} \\
U(1,2) &= 2 + \phi + \lambda + \varepsilon_{11} \\
U(2,1) &= 1 + 2\phi + \lambda + \varepsilon_{12} \\
U(1,1) &= 1 + \phi + \varepsilon_{11}
\end{aligned} \tag{2}$$

Given the action of the computer player, $a_2 (a_2 = 1, 2)$, the human player is assumed to maximize his/her utility function. Therefore, allocation $(a_1^N, a_2)$ is a Nash equilibrium if

$$U(a_1^N, a_2) > U(a_1, a_2), \quad (a_1^N, a_2 = 1, 2),$$

and action $a_1$ is different from action $a_1^N$. Therefore, the Nash equilibrium is determined by the sign of the following utility differences (reaction functions):

$$\begin{cases}
U(2,2) - U(1,2) = \phi - \lambda + \varepsilon_{12} - \varepsilon_{11} \\
U(2,1) - U(1,1) = \phi + \lambda + \varepsilon_{12} - \varepsilon_{11}
\end{cases} \tag{3}$$

From Equation (3), we know that the utility differences are only related to the emotion coefficients. For convenience, let $\varepsilon = \varepsilon_{11} - \varepsilon_{12}$, and $\varepsilon$ follows a logistic distribution. Then, the conditions for the occurrence of pure strategy Nash equilibrium (four observable results) are shown in Table 1. There are multiple

Table 1. Conditions of Nash equilibria.

| Computer \ Human | $U(2,2)>U(1,2)$ and $U(2,1)>U(1,1)$ $\varepsilon<\phi+\lambda$ | $U(2,2)>U(1,2)$ and $U(2,1)<U(1,1)$ $\phi+\lambda<\varepsilon<\phi-\lambda$ | $U(2,2)<U(1,2)$ and $U(2,1)<U(1,1)$ $\varepsilon>\phi-\lambda$ |
|---|---|---|---|
| $P\{a_2=2\}=q$ | (2, 2) | (2, 2) | (1, 2) |
| $P\{a_2=1\}=1-q$ | (2, 1) | (1, 1) | (1, 1) |

equilibria in the interval $\varepsilon\in(\phi+\lambda,\phi-\lambda)$, and we assume that equilibrium occurs according to the probability $q$.

Because the computer chooses randomly following the fixed probability, independent of the choice of the human player, the probability of Nash equilibrium $P\{(i,j)\}$ can be calculated according to the independence of the probability. When $R$ independent results are observed in the experiment, the likelihood function is:

$$L(\phi,\lambda)=P\{(2,2)\}^{n_{22}}\ P\{(1,2)\}^{n_{12}}\ P\{(2,1)\}^{n_{21}}\ P\{(1,1)\}^{n_{11}} \tag{4}$$

where $n_{ij}$ is the number of action combinations $(i,j)$ in the total $R$ independent results, $i,j\in\{1,2\}$, and $\sum_j\sum_i n_{ij}=R$. Then, the maximum likelihood estimators of parameters $\phi,\lambda$ are:

$$\begin{cases} \hat{\phi}=\dfrac{1}{2}\left(\ln\dfrac{n_{22}}{n_{12}}+\ln\dfrac{n_{21}}{n_{11}}\right) \\[2mm] \hat{\lambda}=\dfrac{1}{2}\left(\ln\dfrac{n_{21}}{n_{11}}-\ln\dfrac{n_{22}}{n_{12}}\right) \end{cases} \tag{5}$$

According to Equation (5), if $\dfrac{n_{22}}{n_{12}}=\dfrac{n_{21}}{n_{11}}$, then $\hat{\lambda}=0$. In the experiment, the two players choose at the same time, and the choices of human players should be independent of the computer's choice. There should be no statistically significant difference between $\dfrac{n_{22}}{n_{12}}$ and $\dfrac{n_{21}}{n_{11}}$, so we predicted that $\hat{\lambda}=0$ in our study.

## 5. Results

In WAEG, MAEG and SAEG, the frequencies of the human players' choosing action 2 were 0.38, 0.46, and 0.51, respectively. When the environment's degree of altruism increased, the altruistic behaviors of the human players also increased. As shown in Table 2, for the first round, the computer's choice and the environment's altruism degree have no significant influence on the human players' choices. For the last 10 rounds (each choice round can be regarded as independent because the computer chooses randomly), the altruism degree of the environment has a significant influence on the human players' choices, but the computers' choices in the current round still do not have a significant effect. Once they understood the environment's degree of altruism, the behavior of the

human players changed.

Since the human players' behaviors in the first round did not differ across WAEG, MAEG and SAEG, we combined the three sets of data to calculate the altruism coefficient and inequality aversion coefficient according to Equation (5), as shown in Table 3. Table 3 also shows the altruism coefficient and inequality aversion coefficient for the last 10 rounds in WAEG, MAEG and SAEG. The inequality aversion coefficients are all close to 0 and not significant, in line with our theoretical expectations. In the first round, the human players show higher willingness to be altruistic, despite that their computer opponents do not gain real payoffs. Once they understand the environment's degree of altruism, the human players' willingness to be altruistic is reduced in all three kinds of environments; the altruism coefficients are no more than 0, SAEG is the largest and WAEG is the smallest. The more altruistic the environment is, the higher the willingness of the human players to choose the altruistic action, which shows the human players' unilateral emotional reciprocity between the human players and the exogenous environment (the computer players). Moreover, we also found that even in a strongly altruistic environment, the opponent chose altruistic actions with a probability greater than 50%, but the human players showed no special preference for action 2; they did not have the same willingness to choose altruistic actions as the computers.

## 6. Conclusion and Discussion

In this study, we measure the degree of people's pure emotional reciprocity at

**Table 2.** Binary logistic regression (dependent variable: the human player's choice in the current round).

| Independent variable | | The first round | | The last 10 rounds | |
|---|---|---|---|---|---|
| | | b | sig | b | sig |
| Group | WAEG | | 0.589 | | 0.000 |
| | MAEG | −0.118 | 0.692 | 0.543 | 0.000 |
| | SAEG | 0.196 | 0.532 | 0.710 | 0.000 |
| The computer's choice in current round | | 0.243 | 0.338 | 0.003 | 0.968 |
| Constant | | 0.382 | 0.092 | −0.804 | 0.000 |

**Table 3.** Altruism and inequality aversion coefficients in WAEG, MAEG and SAEG.

| | The first round WAEG, MAEG and SAEG | The last 10 rounds | | |
|---|---|---|---|---|
| | | WAEG | MAEG | SAEG |
| $\phi$ | 0.53 (4.42) | −0.78 (−11.14) | −0.25 (−3.57) | −0.07 (−1.00) |
| $\lambda$ | 0.14 (1.17) | −0.03 (−0.43) | −0.03 (−0.43) | 0.06 (−0.86) |
| Log-likelihood | −189.31 | −593.74 | −657.26 | −664.02 |

T-value in parentheses.

the group level. When the opponent chooses randomly, the subjects' willingness to be altruistic increases with an increase in the degree of altruism in the environment, but it will not increase to the same degree. This may be attributed to the fact that the opponent does not evaluate (reward or punish) the behavior of the subjects (Becker, 1974). The environment will influence people and resonate with their emotions, but it is insufficient to stimulate more altruistic behaviors through emotional influence alone, even if altruistic behaviors are costless. Altruistic behavior is conducive to social harmony and stability. This paper can help us better understand the causes of costless altruistic behavior, which is helpful for the choice of management means and mechanism design and provides ideas and references for creating a good environment.

Although in the model, we consider the possible emotional utility due to different payoffs of both players, we failed to measure the level of inequality aversion of the human players because the two players in our experiments chose at the same time. Having measured simple reciprocity, further experiments could be conducted, such as allowing the computer to choose first. In this way, the influence of the environment and inequality aversion on subjects' behaviors can be both considered.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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# Appendix

**Table A1.** Gender and major of players by experimental treatments.

|  |  | WAEG | MAEG | SAEG |
|---|---|---|---|---|
| Gender | Male | 22.9% | 25.0% | 25.0% |
|  | Female | 77.1% | 75.0% | 75.0% |
| Major | Science | 49.0% | 33.3% | 44.8% |
|  | Social | 31.3% | 36.5% | 35.4% |
|  | Humanities | 19.8% | 30.2% | 19.8% |
| Total number |  | 96 | 96 | 96 |