Seeing is "behaving": Using the revealed-strategy approach to understand cooperation in social dilemma

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Abstract

Identifying heterogeneous decision rules is of fundamental importance in social science research. In this paper, we introduce a data-driven method to capture individual's unique behavioral pattern in social dilemma experiments. The principal idea of the method is that a person's **strategy profile**—a reliable tendency of how one makes decisions in interactive settings— should be revealed by analyzing a series of observed decisions. We demonstrate this revealed-strategy approach in a repeated public goods game. Using unsupervised machine learning, we classify participants' strategy profiles into five distinctive and stable types, which are free-riders, strong cooperators, lower-than-signal cooperators, higher-than-signal cooperators, and hump-shaped cooperators. Hump-shaped cooperation, previously only found using expressed preference (i.e., strategy method), is first identified as an observed behavioral pattern in repeated games using the revealed-strategy approach. In two simulations, we show that policies utilizing how conditional cooperators respond to the norm can effectively promote cooperation. We encourage future research to extend the revealed-strategy approach to quantify and understand the heterogeneous mixture in diverse contexts.

Key words: Revealed-strategy, behavioral heterogeneity, social dilemma, machine learning

1. Introduction

Behavioral heterogeneity, that people differ in their decisions, responses, beliefs, or preferences given the same economic and social situation is prevalent in human society. Identifying heterogeneous behavioral patterns is crucial to describe, predict, and interpret decisions in empirical studies and real life, and therefore, is of fundamental importance in social science research. As Heckman (2001) stated in his Nobel Lecture: “This heterogeneity has profound consequences for economic theory … Accounting for heterogeneity and diversity and its implications is a main theme of my life’s work”. In this paper, we aim to contribute to Heckman’s research agenda, introduce a data-driven method to help better understand heterogeneous in human decision-making.

Consider cooperation decision as an example. In a variety of situations, people face the social dilemma between keeping limited resources to themselves and contributing to the public to improve collective welfare. Such cooperation among self-interested individuals has been a main focus in economics and behavioral research. In the literature, public goods games have been widely used to understand cooperation decisions. One clear finding emerged from past studies is that people vary substantially on their behavioral patterns when facing cooperation decisions (Burlando and Guala, 2005; Fischbacher et al., 2001; Goerre et al., 2005; Kurzban and Houser, 2005). Further, we have learned that most people make their cooperation decisions in accord with their beliefs about (or observations of) others' decisions (i.e., conditional cooperation) (Fischbacher and Simon, 2010; Fischbacher et al., 2001; Keser and Winden, 2000). (Fischbacher and Simon, 2010; Fischbacher et al., 2001; Keser and Winden, 2000). However, the behavioral patterns in public goods game are exceptionally difficult to capture, as people may differ considerably on how they respond to others (Burlando and Guala, 2005)[1]. Most studies in heterogeneous decision-making have to pre-specify a set of behaviors of interest, and then assign each subject with one of these behavioral types. But the question of how to empirically characterize and justify for these types

[1] A wide range of terms have been used to describe different levels of cooperation of the conditional cooperators (Fischbacher et al., 2001; Keser and Winden, 2000; Rustagi et al., 2010) (e.g., strong/weak free-riders/cooperators, weak or imperfect conditional cooperators; and hump-shaped players, reciprocators).

remains unanswered. Up to today, we have not found a method that can help to systematically and comprehensively identify the existing (and the hypothesized) behavioral types scattered in the empirical data and in reality.

In this paper, we propose a revealed-strategy method to capture behavioral heterogeneity in social dilemma. We put forward that a person's **strategy profile**—a reliable tendency of how one makes decisions in interactive settings— should be revealed by analyzing a series of observed decisions. We use a repeated public goods game as an example to demonstrate how to apply the revealed-strategy approach to identify heterogeneous behavioral patterns. Our public goods game experiment adopted a random-matching design. In total 252 undergraduate students participated in the experiment. They were asked to allocate 10 hours of weekend time. In each round of the repeated game, participants made a decision about how many hours they would contribute to a group project as opposed to keep to themselves. For payoff, every hour spent on the individual project yields 20 game points; every hour spent on the group project yields 40 game points. At the end of each round, all participants in the same group receives an equal share from the public goods (i.e., group-effort project). The game was designed with a random-end mechanism and lasted at least twelve rounds. In the first round of the game, all participants made the contribution decision without knowing what other people did. In later rounds, we presented participants with a *signal*—the average contribution of the previous group they were in—before they decided their own contribution (see details in ***S1.* Experimental Design and Administration**).

2. Key Elements of the Strategy Profile in Repeated Public Goods Game Setting

To construct a person's strategy profile, we draw on (Lewin, 1943)'s classic conceptualization that behavior is a product of the **person** and the **environment**. In particular, Lewin suggested that in order to understand the decision-making mechanism, we need to consider how the decision-maker address an issue without any external influence and how the same person react to the surrounding environment. In addition, we also extend the notion that factors influencing one's behavioral pattern, rather than just a single observable behavior, should be incorporated in modeling heterogeneity (Pennings and Garcia, 2004). Specifically, we first consider how one makes decisions independent of other people. In round one, everyone decided their contribution without knowing what others did (*first round contribution*). We recognize that the first round behavior may be fundamental to one's average contribution in a repeated game (Keser and Winden, 2000). We do not, however, assume that higher first round contributions indicate higher willingness of cooperation, or vice versa, because it is only part of one's strategy profile. Next, we identify indicators of how one respond to other people during the iteration. Starting from round two, we presented participants with a signal—the average contribution of the previous group they were in—before they decided their own contribution. We then divided a person's next round contribution by the signal that person received to construct a *contribution to signal ratio* (short as *ratio* below) to capture how one might be influenced by the environment. During the repeated game, this ratio for each individual may change from round to round. Therefore, it is also crucial to look at the *variability of the ratio* over time.

In sum, we constructed an individual's strategy profile in the repeated public goods game using three indicators: first-round contribution, average ratio (i.e., contribution to signal ratio), **and the variance of the ratio.** The first-round contribution reflects one's unconditional contribution without knowing what other people would do. The magnitude and stability of the ratio together indicate conditional behavior patterns. To classify participants into distinct cooperative strategy types, we used an unsupervised machine learning algorithm (i.e., hierarchical clustering), in which the Euclidean distance indicates similarity of all possible pairs of strategy profiles for grouping. Next, we used the dendogram from the clustering analysis to identify distinct types of behavioral patterns. The detailed procedure and algorithm is presented in ***S3.* Algorithm in Unsupervised Machine Learning**. Worth mentioning, we do not claim this is the only way to construct a person's strategy-profile. Other constructions of the strategy-profile could be potential extensions of the current study. However, we do want to emphasize that the strategy-profile should be as simple as possible, so that it only captures the essential characteristics of the behavioral pattern.

There are three major advantages of using this method to classify behavioral types. First, it does not require us to pre-specify possible types in the data; accordingly, we don't need to make any arbitrary assumptions about the subjects' possible motivation or preferences. Second, this approach is simple and easy to apply. Third, as we will show below, it can deliver very fruitful results that could be used to conduct further analysis.

3. Five Heterogeneous Strategy Patterns

Based on our laboratory experiment and evidence observed in past studies, we identified five heterogeneous patterns in how people make cooperation decisions. The five types include: free-riders (13.65% of the sample, short as *FR* below), lower-than-signal cooperators (32.53% of the sample, short as *LC* below), higher-than-signal cooperators (32.13% of the sample, short as *HC* below), strong cooperators (11.25% of the sample, short as *SC* below), and hump-shaped cooperators (10.44% of the sample, short as *HS* below). The unconditional contribution (i.e., *first-round contribution*) of each type of players is listed in Table 1. Moreover, we calculated the average *ratio* of each participant. In our sample, this average *ratio* is normally distributed with a mean value of 1.01 (s.d. = 0.35), suggesting that people did vary in their responsiveness to the signal. The distribution of the average *ratio* is indicative of heterogeneous response patterns (Figure 1).

Table 1. First-round Contribution (unconditional behavior) of Each Type

First-round Contribution (% of endown.)	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Free-riders (FR)	12%	18%	12%	38%	18%	3%	0%	0%	0%	0%	0%
Lower-than-signal Cooperators (LC)	0%	0%	0%	1%	4%	35%	19%	12%	10%	1%	19%
Higher-than-signal Cooperators (HC)	0%	0%	4%	18%	31%	29%	15%	4%	0%	0%	0%
Strong Cooperator (SC)	0%	0%	0%	0%	0%	11%	11%	11%	14%	4%	50%
Hump-Shape Cooperators (HS)	38%	4%	27%	15%	8%	4%	4%	0%	0%	0%	0%

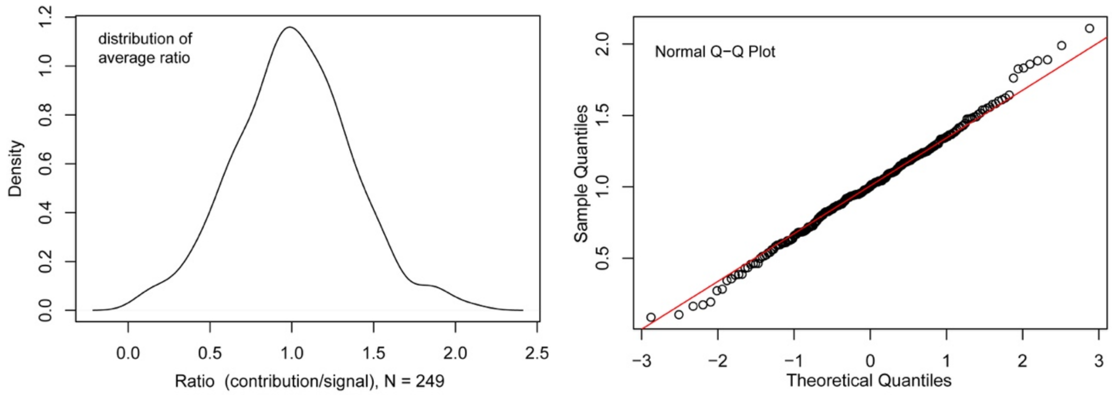

Figure 1. Average ratio normally distributed

Figure 2 shows the contribution to signal ratio over time for each type, in which a value of one on the y-axis reflects perfect conditional cooperation (i.e., contribution is identical to the signal in every round). Results show that most people were not perfect conditional cooperators. We found consistent strategies that were oriented toward free-riding (i.e., lower-than-signal cooperators) and toward being more cooperative (i.e., higher-than-signal cooperators). In particular, we found a strategy pattern in which the ratio is keep changing from round to round, and the variance of the ratio is much larger than all other strategy patterns. This type of strategy pattern seems to very responsive to the signal, yet in opposite directions (i.e., the hump-shaped cooperators).

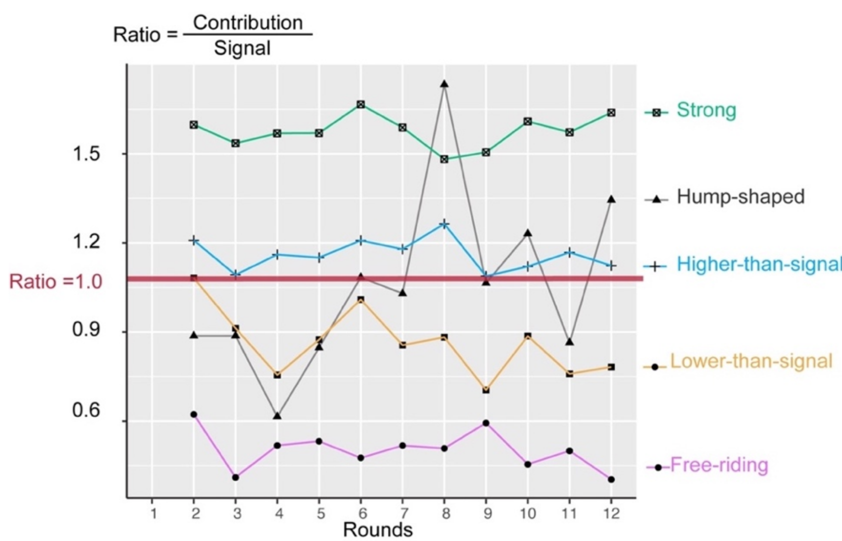

Figure 2. Contribution to signal Ratio over time

Table 2 illustrates variables in the strategy-profile for each player type. Figure 3 shows the relationship between the participants' average contributions and the average signal they received in each round for all types. From these results, we found that Free-riders (*FR*) contributed significantly lower than the signal (average contribution = 22% of the endowment, average *ratio* = 0.50, s.d. *ratio* =0.36). On the opposite side, strong cooperators (*SC*) consistently contributed significantly higher than the signal (average contribution = 87% of the endowment, average *ratio* = 1.58, s.d. *ratio*= 0.40,).

Table 2. Descriptive Statistics of Different Strategy Profiles

Player Types	Contribution/Signal Ratio		First-round Contribution (% of endowment)	Average Contribution (% of endowment)	Average Earnings (Points)
	average ratio	s.d. ratio			
Free-riders	0.50	0.36	24%	22%	3317
Lower-than-signal Cooperators	0.86	0.60	66%	41%	3023
Higher-than-signal Cooperators	1.16	0.46	45%	52%	2791
Strong Cooperator	1.58	0.40	84%	87%	2558
Hump-Shape Cooperators	1.05	1.11	18%	40%	2959

For the conditional cooperators, the average ratio of the lower-than-signal cooperators (*LC*), higher-than-signal cooperators (*HC*), and hump-shape cooperator (*HS*) were 0.86, 1.16, and 1.05. Their first-round contributions were 66% (*LC*s), 45% (*HC*s), and 18% (*HS*s) of their initial endowment. Both the average per-round contribution ratio and the first-round contributions of all different types were statistically significantly different (pairwise mean comparison test result, $p<0.01$)[2]. The average amount of contribution across all rounds were 41.4% for *LC*s, 51.5% for *HC*s, and 40.0% for *HS*s. These results suggest that using first round contribution to indicate consistent cooperative preference might be inconclusive. Moreover, if we only look at the aggregate contribution, the *HS*s are undistinguishable from the *LC*s. In addition, we found that the difference in average earnings associated with each strategy profile were all statistically significant (pair-wise mean tests results: $p<0.001$). These results indicate that the five types of strategy profiles are substantially distinct from one another.

[2] The only exception is when comparing the mean ratio of *HS* and *HC*. The p-value is 0.108.

Table 3. The Hump-Shaped Cooperators Alter Contribution Conditional on the Signal

Signal	Contribution to Signal Ratio (for each type of players)				
	Strong cooperator	Higher-than-signal cooperator	Lower-than-signal cooperator	Free-riders	Hump-shaped cooperator
0-20%	NA	1.70	1.33	0.38	3.13
20%-30%	2.93	1.48	0.99	0.67	1.41
30%-40%	2.02	1.24	0.99	0.51	0.95
40%-50%	1.77	1.12	0.76	0.57	1.01
50%-60%	1.65	1.06	0.80	0.49	0.81
60%-70%	1.45	1.06	0.83	0.30	0.66
70%-80%	1.24	0.99	0.85	0.42	0.89
80%-100%	1.15	1.05	0.77	0.45	0.97

To further examine the relationship between the contribution decision and the signal, Table 3 lists each play's ratio conditional on different signal. From Table 3, a notable finding is that the hump-shaped cooperators showed high responsivity to the signal, yet in alternating directions. In particular, when the signal was lower than or equal to 50% of the initial endowment, the hump-shaped cooperators contributed more than the signal; when the signal was higher than 50%, the hump-shaped cooperators switched to contributing lower than the signal. It is worth noting that the hump-shaped type has only been theoretically discussed and identified using the expressed preference method (or strategy method, e.g., Selten, 1967) previously. Our revealed-strategy approach first empirically identified this type of players in repeated public goods game.

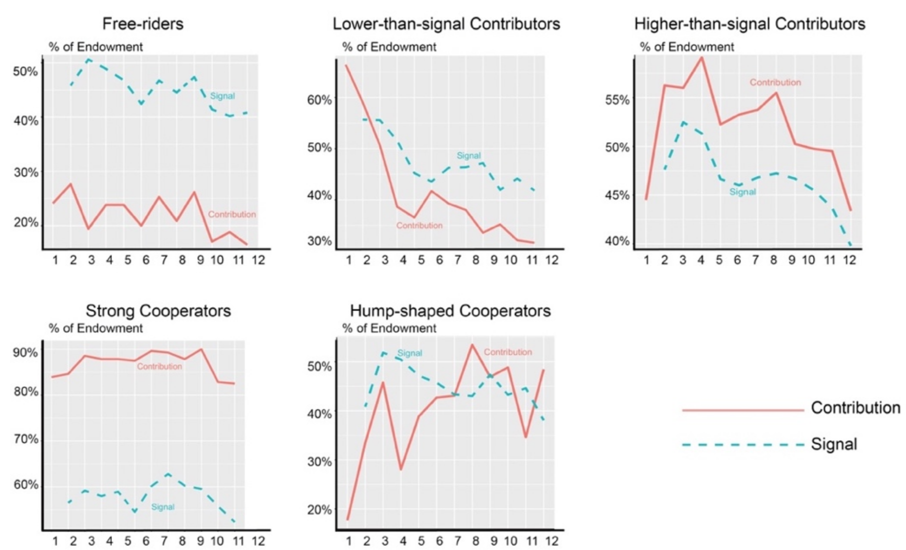

Figure 3. Signal is an Important Reference of Contribution Decision

To examine if an individual's strategy profile is consistent, we performed two non-parametric tests (Kolmogorov-Smirnov test and Mann-Whitney test). In particular, for an individual classified as a specific type, we want to know if the distribution of this person's *ratio* (11 decisions over time) follows the type's distribution she is in. Test results (Table 4) indicate that more than 82% of the participants' strategies are consistent with their types.

Table 4. Proportion of Individuals Who Passed the Consistency Test

	Kolmogorov-Smirnov (p=0.01)	Mann-Whitney (p=0.01)
Free-riders	82%	79%
Lower-than-signal Cooperators	80%	86%
Higher-than-signal Cooperators	80%	79%
Strong Cooperators	79%	79%
Hump-shaped Cooperators	88%	88%
Total	82%	82%

Kurzban and Houser (2005) pioneered in classifying systematic decision rules in strategic games. In a repeated public goods game, the authors demonstrated a Linear Contribution Profile (LCP) method to model behavioral patterns and cooperation types[3]. Within the revealed-strategy approach, we aim to model people's contribution decisions as an evolutionary, changing process **with systematic patterns**. As a consequence, the revealed-strategy approach provided a more detailed result, and increased the richness of the classification outcome. Table 5 compares the classification results from the LCP and the Revealed-strategy approach. Under the LCP method, about 10% of the sample data has to be dropped, as they do not belong to any pre-specified types; Under the revealed-strategy approach, every subject could be assigned into a type, simply based on the similarity of the strategy profiles. Moreover, we can see there are many overlaps between these two classification results. For subjects who belong to "cooperators" under the LCP method, 62% (23/37) of them were identified as strong cooperators, and 32% (12/37) were identified as higher-than-signal cooperators under the revealed-strategy approach. For subjects who belong to "free-riders" under the LCP method, 44% (22/50) of them were identified as free-riders, and

[3] Specifically, the LCP method demonstrated that we may learn about how a people make decisions in the public goods game by regressing one's contributions on the observed contributions from the others across several rounds. Given the parameters (i.e., intercept and slope) from the regression analysis, one can construct the LCP to capture one's decision pattern: the intercept in the LCP indicates one's willingness to cooperative, and the slope in the LCP indicate how one respond to the others.

34%(17/50) of them were identified as lower-than-signal cooperators under the revealed-strategy approach. For subjects who belong to "conditional cooperators" under the LCP method, 83% (113/136) of them were identified as either higher-than signal or lower-than-signal cooperators. Results from the revealed-strategy method identified more detailed, systematic behavioral patterns using a simple and fast algorithm.

Table 5. Results from the Revealed-Strategy Approach and the LCP Method

		The Revealed-Strategy Approach					
		FR	HS	LC	HC	SC	Total
LCP method	Type 1:Cooperators	0	2	0	12	23	37
	Type 2:Conditional players	10	8	54	59	5	136
	Type 3:free-riders	22	7	17	4	0	50
	dropped	2	9	10	5	0	26
	Total	34	26	81	80	28	249

Another question we are interested in is how varying mixture of heterogeneous types in the population determines the total social welfare (e.g., aggregated overall contribution). Since we conducted 14 sessions with 18 participants in each, we considered each session as a "mini society". Table 6 describes the sub-sample mixture, average contribution, and average earnings in each session. To better illustrate the role of the mixture, we took the comparison of two particular sessions as an example: session 1 and session 12. In session 1, the majority of the participants were lower-than-average cooperators (44% of the population). In session 12, the majority of the participants were higher-than-average cooperators (50% of the population). That is to say, most participants in session 1 tended to contribute relatively less than the norm they saw; whereas most participants in session 12 tended to contribute relatively more than the norm. However, the average contribution in session 1 is 96% higher than in session 12. The average payoff in session 1 is 3291 game points, which is significantly higher than the average payoff in session 12 (2659 game points; pair-wise mean tests results: $p<0.001$). Notably, strong cooperators took 28% of the population in session 1 but only 6% in session 2. Free-riders took 6% in session 1 but 22% in session 12. In session 1, the average contribution from the *LC*s was 57% of their endowment. Although the *LC*s in this session chose to contribute less than the norm of their peer, in an environment where many others exhibit cooperating behaviors, even the *LC*s made considerable contributions. In contrast, the average contribution from the *HC*s in session 12 was 41% of the endowment. Thus, a society that free-riding appeared to be salient impeded *HC*s from making more contribution; whereas a society that strong cooperators were salient promoted cooperation. These results suggest a clear impact of highly cooperative individuals (relative to the free-riders) on the sub-types of conditional cooperators that have been overlooked in past studies.

Table 6. Population Mixture and Average Payoffs in Each Session

Session	FR	LC	HC	SC	HS	Average Contributions (% of endowment)	Average Earnings (Points)
01	6%	44%	17%	28%	6%	65%	3291
02	6%	56%	22%	0%	17%	41%	2814
03	11%	39%	28%	11%	11%	56%	3133
03	17%	6%	28%	28%	22%	60%	3207
04	6%	39%	28%	0%	28%	30%	2660
05	6%	39%	44%	11%	0%	43%	2867
06	11%	50%	28%	6%	6%	49%	2982
07	13%	20%	60%	7%	0%	43%	2787
08	28%	28%	22%	17%	6%	46%	2918
09	11%	39%	28%	11%	11%	48%	2965
11	11%	39%	39%	0%	11%	46%	2925
12	22%	17%	50%	6%	6%	33%	2659
13	28%	22%	22%	28%	0%	57%	3145
14	17%	17%	39%	6%	22%	35%	2698

4. Application: Agent-based Simulation

Upon identifying heterogeneous behavioral patterns, we now demonstrate an application of utilizing the revealed-strategy approach: to help perform agent-based simulations and test the impacts of certain policies. Agent-based simulations are widely used in studying the dynamic of strategic interactions. In the realm of social dilemma, identifying and clarifying the simulated agents' types and the associated decision rules has been a difficult task for social science researchers (Kurzban and Houser, 2005). For instance, one commonly acknowledged phenomenon in social dilemma is that social norm plays a vital role in shaping cooperation (Fehr and Fischbacher, 2004, Centola et al., 2018). However, since little is known about how the conditional cooperators may respond to a given norm, it is remarkably challenging to theoretically model their norm-abiding, yet heterogeneous behaviors. (Burlando and Guala, 2005).

Using the revealed- strategy approach, the classification results generated from our study can shed light on how to model the heterogeneous agents, and further allows us to investigate how social norm policies differentially impact each type of players. In line with the view that conditional cooperation represents conformation to normative behaviors (Fehr and Fischbacher, 2003), we demonstrate that 1) targeting subtypes of conditional cooperators for norm enforcement can be a promising avenue to increase cooperation; 2) the same policy may have varied or even opposite impacts on different types of players.

Increasing cooperation in general is an important mission for social change in many domains, such as collective actions to combat climate change and pollution (Tankard and Paluck, 2016). In public goods games, sustaining voluntary cooperation without implementing punishment or reward has been one primary challenge (Chaudhuri, 2010). Extensive research showed that presenting simple descriptive information on normative behavior can foster people to act similarly (e.g., Nolan et al., 2008). Moreover, much of policies implement a short and effective amount of stimulation, and then start taking effect by triggering a "tipping point"— when the majority of people adopt a previously uncommon practice as this minority practice reach 25% of the population (Centola et al., 2018). These studies imply that targeting types more responsive to the treatment may promote social change more effectively, because the social interactions among malleable heterogeneous types are powerful to influence others' behaviors. In sum, people with conditional cooperative strategies should be most responsive to the norm. Yet little is known about how each sub-types of the conditional cooperators may respond to the descriptive norm information.

In two simulations, we demonstrated that a one-instance presentation of a higher norm (i.e., presenting a signal higher than the actual signal in round two of the public goods game) could result in greater contributions over time compared to no change to the norm (i.e., presenting the actual signal resulted from the average contribution of round one). Additionally, the total social welfare could be increased dramatically because of the increase in aggregated cooperation level. We build agents to represent the five types revealed from the experimental data. In particular, let's use $\boldsymbol{C_{i,t}}$ denotes type i agent's contribution in round t, $\boldsymbol{first_i}$ denotes type i agent's first-round contribution (i.e., unconditional decision), $\boldsymbol{signal_t}$ denotes the signal in round t, and $\boldsymbol{ratio_{i,t}}$ denotes type i agent's *contribution to signal ratio* in round t. In general, a simulated-agent's contribution in each round is given by:

$$C_{i,t} = \begin{cases} first_i, & t = 1 \\ signal_t \times ratio_{i,t}, & t \geq 2 \end{cases}$$

specific parameters were determined by non-parametric estimations based on data collected from the laboratory experiment (The detailed algorithm and estimation procedure could be found in ***S4.* Simulation Study**). Next, we generate a "societies" in which the population mixture is the same as in the laboratory experiment. i.e., each type of simulated players account for the same proportion as in the lab experiment. In Simulation 1, the simulated agents played exactly the same public goods game as in our laboratory experiment. In Simulation 2, we introduce the one-instance change in the descriptive norm at the end of round one. Specifically, we doubled the average contribution in each group and then send the modified signal to the players[4]. All other settings were the same as in Simulation 1. In each scenario, we carried out 1000 simulated experimental sessions. We then compared the contributions and payoffs from these two simulated scenarios.

[4] One can imagine this policy as a one-time government investment that matches the total fund raised from individual firms. However, we should note that what is being modified here is the "social perception", rather than a lump-sum payment. There are many possible ways to double the perceived social norm. For example, the policy maker can also send a signal that most people is willing to cooperate by present past history.

Table 7. The One-instance Change in the Signal Improve Social Welfare

	WITHOUT Policy Intervention		**WITH** Policy Intervention		Changes in contribution	Changes in payoffs
	Average Contribution (% of endow.)	Average Earnings (Points)	Average Contribution (% of endow.)	Average Earnings (Points)		
FR	24%	2937	24%	3139	0%	+6.9%
LC	31%	2877	40%	2976	29%	+3.5%
HC	48%	2688	59%	2768	23%	+3.0%
HS	14%	3066	12%	3281	-14%	+7.0%
SC	87%	2239	87%	2433	0%	+8.7%

Table 7 summarizes and contrasts results from the two simulations. All types of players were better-off in the society with the policy intervention occurred in round two. The average improvement in social welfare was approximately 6%. The compared average contribution level and change in total social welfare is shown in Figure 4. It is worth noting that average contributions from *FR*s and *SC*s had no change in the two simulations, since their strategies were independent from the "signal" they received. Both of these two types would behave unconditionally to what other people did. In contrast, with a one-instance increase in the signal, *LC*s and *HC*s contributed more than without the policy (29% increase for *LC*s and 23% increase for *HC*s). However, the *HS*s contributed 14% lower than before. The decrease in *HS*s' contributions was due to their unique strategic decision-making rule: contributing less when others do more, and contributing more when others do less. This result indicates that the change in descriptive norm policy can effectively improve total social welfare. This type of policy predominantly works by nudging *HC*s and *LC*s to contribute more. However, because this policy does not take strategic responses (i.e., *HS*s make contribution in the opposite direction of the norm) into consideration, it leads the *HS*s to be less cooperative than when there is no policy. Finally, although the policy increased overall contribution, its impact declined overtime. This suggests that sustaining the impact of policy requires to counteract decision rules (i.e., *HS*s and *LC*s) that may resist the policy.

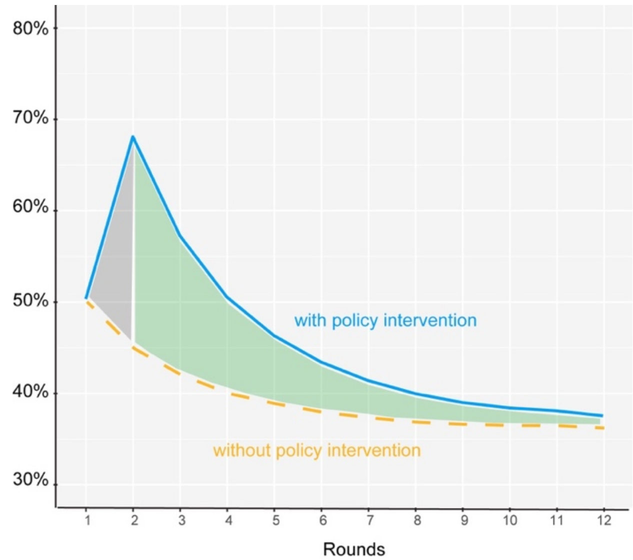

Figure 4. Policy intervention promote cooperation and social welfare

5. Discussion

In this paper, we proposed the revealed-strategy approach to improve classification of behavioral heterogeneity in social dilemma studies. Using a repeated public goods experiment as an example, we demonstrate that this approach has major theoretical and practical contributions to the literature on cooperation in social dilemma. In particular, we found three sub-types of conditional cooperators: lower-than-signal cooperators, higher-than-signal cooperators, and hump-shaped cooperators. Uncovering these subtypes could contribute to research on sustaining and increasing contribution in public goods games: it settles inconsistencies of past research on why conditional cooperators are sometimes more influenced by free-riders but other times more so by strong cooperators (Chaudhuri and Paichayontvijit, 2006; Fischbacher and Simon, 2010; Fischbacher et al., 2012; Keser and Winden, 2000; Rustagi et al., 2010). Moreover, past studies suggested that the varying mixture of different strategy types in a population could substantially alter the aggregated contribution (Camerer and Fehr, 2006). Our results not only confirmed this finding, but further explained how exactly the mixture of the heterogeneous agents may lead to predictable social outcomes.

We identified the hump-shaped cooperators in repeated public goods game for the first time. Fischbach et al. (2001) theorized “hump-shaped” players as people who initially contribute almost identically as others and then decrease their contributions once others’ contributions exceed 50% of the endowment. In this study, we found that hump-shaped cooperators contributed in opposing direction to the signal in a multi-player, multi-round process. They made high contribution when the signal was below 50% of the endowment and low contribution when the signal exceeded 50% of the endowment. This alternating pattern is consistent with tactical reasoning behind reciprocity (Gouldner, 1960), which might suggest people may tactically contribute more in order to make others contribute more. Hence, the revealed-strategy approach can uncover more heterogeneous behavioral patterns that are new empirical evidence of diverse theories on cooperation.

Further, the revealed-strategy approach can be utilized in simulation studies that offer insights to policy-making. We simulated policies that target how people may respond to a descriptive norm (i.e., average contribution by others) without knowing or attempting to change cooperative preferences or beliefs. Our simulation results suggest that it is more effective to target the conditional cooperators for social change. We showed the effectiveness of presenting a larger average contribution in promoting total social welfare. This positive social change is primarily due to increased contribution from conditional cooperators (*HC*s and *LC*s). However, the same policy may lead the hump-shaped cooperators decrease their contribution and counteract the intended impact of the policy. Policy makers should take into consideration that the same policy may have different (or even opposing) impact on people adopting distinct decision rules.

In addition to social dilemmas, examples are found in consumer behaviors (Caselli and Ventura, 2000), hedging behaviors (Pennings and Garcia, 2004), and dynamic search behaviors (Schunk, 2009). Most past empirical studies in behavioral heterogeneity regress observed decisions on a set of explanatory factors (i.e., personality traits, demographic information, etc.), and then infer how people differ in decision rules (Athey and Imbens, 2015). Such regression method is effective in situations where the focal interest is constrained to a single observed behavioral outcome. However, in dynamic situations where multiple decisions are made during repeated, interactive iterations, the regression method often have to make simplified assumptions, and therefore oversimplifies the underlying decision-making process (Houser et al., 2004). The revealed-strategy approach may complement established methods focusing on inferring motivations and beliefs from observed behaviors (i.e., revealed-preference method) by modeling decision processes in dynamic interaction. This way, the heterogeneous strategy patterns may help construct utility functions that are more consistent with real-world behaviors[5].

To conclude, we suggest that uncovering heterogeneity in behavioral patterns *and* the natural interaction among people differ in these rules are critical steps to select more impactful treatments, policies, and personal characteristics for testing in experiments and fields. The revealed-strategy approach gains insights into behavioral heterogeneity by modeling systematic patterns in observed decisions. We want to promote such thinking that in addition to inferring what people intend to do or what they expect others to do (i.e., thoughts in their minds), we are able to model decision rules from what they actually did and encountered.

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Supplementary Materials

S1. Experimental Design and Administration

The experiment was conducted at Jianghan University in China. A total of 252 undergraduate students from the Business Department participated in our experiment[6]. We administered 14 experimental sessions during 2017 October, each of which consisted of 18 participants. Each session took approximately 60 minutes (including check-in and payment processing). All the sessions were conducted with computer-based materials, which are developed using z-tree (Fischbacher, 2007). During the experiment, all participants earn "points" (the fictitious experimental currency), and at conclusion, four out of twelve rounds[7] were randomly selected to pay the participants. Participants are paid in cash privately at the rate: 1 RMB (=0.16 US dollar) for every 100 points they earn. The average earnings were 30 RMB (including 5 RMB attendance fee)[8].

In this experiment[9], we adopted a random-partner, repeated game setting. In each experimental session, 18 participants were randomly assigned into one of three groups (i.e., six

[6] Our data analysis indicated that three students participated twice. To rule out possible learning effect, we excluded their duplicated data from the analysis. Therefore, our final sample consists of 249 individual observations in total.
[7] The game was designed with a random-end mechanism that allow the participants to interact at least 12 rounds.
[8] At Jianghan University, 30RMB is approximately the cost of 5 single-serving meals in the student dining hall.
[9] It is worth mentioning that we adopted a context closely related to students' daily life for the public goods game. Specifically, we asked participants to complete a time-allocation task. Everyone has 10 hours free-time as initial endowment. A participant allocates the 10 hours on two projects: an individual-effort project, and a group-effort project. A participant's payoff in each round is the sum of payoffs in the two projects.

individuals per group) to play a public goods game. Each participant's payoffs in a round depends on both her decision and all other people's decisions in the same group. After each round, we shuffled the participants and re-assign them into new groups.

At the beginning of each round, the participants received 10 hours as the initial endowment. A participant needed to decide how to allocate the 10 hours between an individual project and a group project. Every hour spend on the individual project yields 20 game points payoffs; every hour spend on the group project yields 40 game points payoffs. At the end of each round, all participants in the same group receives an equal share from the group-effort project. That is, we will divide the total contribution in the group-effort project by 6 (the group size), and then distribute the same share to each group member. To demonstrate the incentive mechanism, we now describe the payoff function. Let Z_i denote the endowment of subject i, C_i denotes the individual contribution to the public goods, m denotes the multiplier of contribution, p denotes marginal return on those part not contributed, N denotes group size. The payoff function for participant i is given by:

$$\pi_i = \left(Z_i - C_i\right)p + \frac{a}{N}\sum_{j=1}^{N} C_i \qquad (1)$$

where: $C_i \leq Z_i$, and $\frac{a}{N} < p < a$

Accordingly, the marginal per capita return (*MPCR*) is defined as:

$$MPCR = \frac{a}{Np} \qquad (2)$$

In our experiment, we choose the parameters as follow: $Z_i = 10, p = 20, a = 40, N = 6, and\ MPCR = \frac{1}{3}$.

In the first round of the game, all participants made the contribution decision without knowing what other people do. In later rounds, we presented participants with a *signal*—the average contribution of the previous group they were in—before they decided their own contribution. This design allows us to describe the ratio of one's contribution relative to the signal, and whether such ratio varies across time. That is to say, during the iteration, the participants saw a "signal" about the social norm prior to the decision phase. Then we shuffled the participants and reassigned new groups. We adopted this design to simulate a scenario where one can observe what other people did, and perhaps infer others' cooperativeness accordingly. The random-partner mechanism prevented with-in group learning from happening.

S2. Descriptive Statistics on Participants' Decisions in the Experiment

Experimental results show that the average contribution in our experiment decayed over time. In the first round, the average contribution was 50.4% of the participants' endowment. This number gradually declined to 40.8% by the end of the game. The average contribution in each period is depicted in Figure S1. This pattern is consistent with the commonly observed pattern in previous public goods experiments.

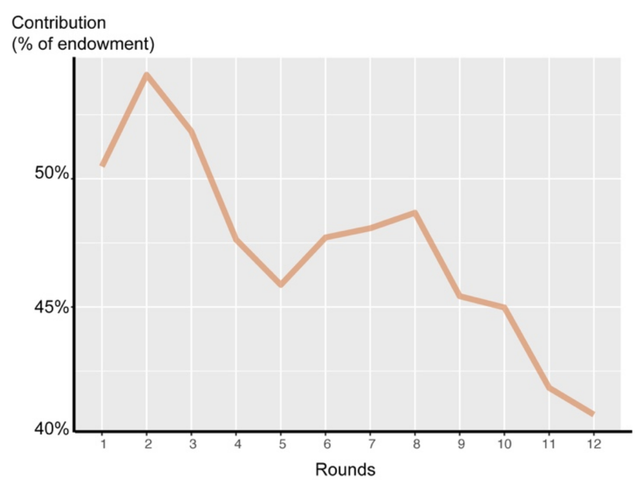

Figure S1. Average Contribution Decayed Over Time

S3. Algorithm in Unsupervised Machine Learning.

Formally, we use $S_k^i = \{ s_1^i, s_2^i, s_3^i, \dots \}$ to denote the type-i player's strategy-profile, which contains k criteria. For example, S_3^i denotes that a set of three behavioral criteria illustrates type-i player's decision-making pattern. In the current context, player i's strategy profile in the repeated public goods game is given by:

$$S_3^i = \{ s_1^i, s_2^i, s_3^i\} \quad (3)$$

where s_1^i is player i's contribution in round one, s_2^i is player i's average ratio during the repetitions, and s_1^3 is the variance of player i's ratio[10].

Having the strategy-profile constructed, the next step is to determine how many different types of strategy-profiles exist. In other words, suppose every participant have her own reasoning and therefore strategy profile, which strategy-profiles are similar enough to be considered as the same "type". For individual i, let consider the strategy-profile S_3^i as a vector. Operationally, we use the Euclidean distance[11] between the vectors to determine the similarity between the profiles. Specifically, the Euclidean distance between two vectors S_3^i , S_3^j is measured by:

$$d\left(S_3^i , S_3^j\right) = \sqrt{(s_1^i - s_1^j)^2 + (s_2^i - s_2^j)^2 + (s_3^i - s_3^j)^2} \quad (4)$$

Based on this distance measure, we then apply Ward's minimum distance method to divide (and assign) individual participants into clusters. Let use $T(t)$ to denote a typology that divides the vectors into t clusters. The Ward's minimum distance method calculates the within-group variance among all possible combinations for any $t = 1, 2, \ldots, i$, and then determines which vectors are close enough to be in the same cluster[12]. Figure S2 depicts the dendogram of the cluster results.

[10] To make the indicators comparable to each other, we standardize each of the variables with the following equation: $s = \frac{(x-\overline{x})}{\sigma}$.

[11] Another distance measure we applied was the Manhattan distance. The results from the M-distance were very similar with results from Euclidean distance. Detailed reports are available upon request.

[12] In addition to the hierarchical clustering algorithm, we also tried the k-means algorithm and Gaussian mixture model algorithm. All methods generated similar outcomes. The results using other algorithms are available upon request.

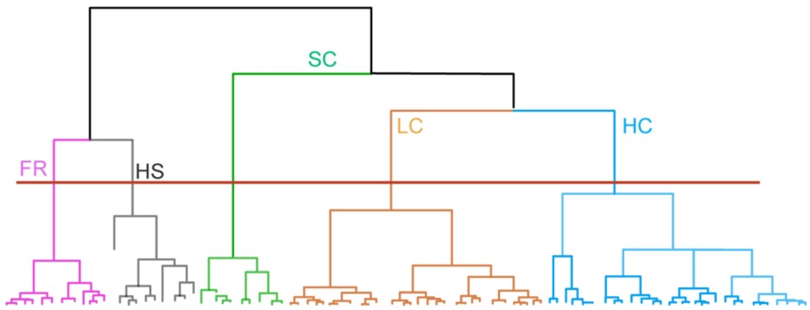

Figure S2. Cluster Dendrogram

S4. Simulation Study

Let's use $\boldsymbol{C_{i,t}}$ denotes type i agent's contribution in round t, $\boldsymbol{first_i}$ denotes type i agent's first-round contribution (i.e., unconditional decision), $\boldsymbol{signal_t}$ denotes the signal in round t, and $\boldsymbol{ratio_{i,t}}$ denotes type i agent's *contribution to signal ratio* in round t. In general, a simulated-agent's contribution in each round is given by:

$$C_{i,t} = \begin{cases} first_i, & t = 1 \\ signal_t \times ratio_{i,t}, & t \geq 2 \end{cases} \tag{5}$$

(1). Simulation of Unconditional Behavior.

In the first round of the experiment, all participants make contributions without knowing information about the others. To simulate this unconditional decision, we used the kernel density estimator to obtain the probability density function of the first-round contribution for each type players. Specifically:

$$\hat{f}(x) = \frac{1}{nb} \sum K(\frac{x - \overline{x}}{b}) \tag{6}$$

where b is the bandwidth and K is the smoothing function[13]. In every simulated session, a simulated-agent's first-round contribution was randomly drawn from the estimated distribution. Thus, we do not assume to know the motivation of your decision (or the unconditional belief). Rather, we simulate what a person may do based on the observed laboratory results. The empirical distributions of each type player's first-round contribution are shown in Figure S3.

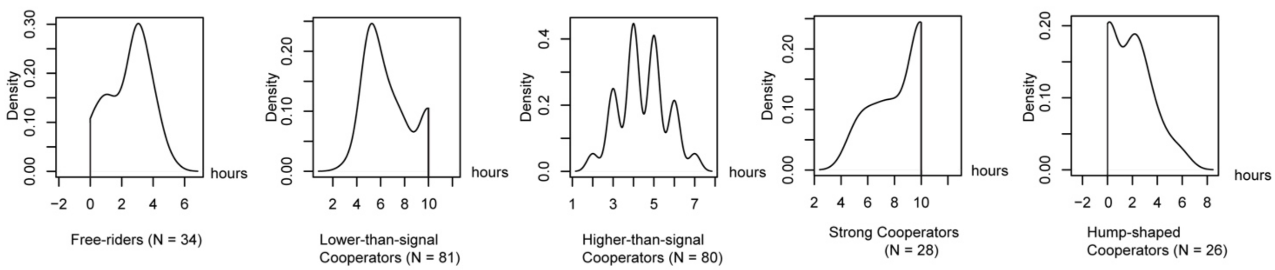

Figure S3. Distributions of First-Round Contributions

(2). Simulation of Conditional Behavior

Start from round 2, the participants see the signal (i.e., group average from previous rounds). Since the influence of past events decline over time, we only focus on how the last round group average influence decisions. From the laboratory experiment, we observed that the free-riders (FR) and the strong cooperators' (SC) decisions were barely influenced by others. In particular, the free-riders always made none or minimal contributions. To emphasize such characteristics, starting from round two, we let the simulated FRs and SCs always make contribution as in round-one (i.e., a random draw from the empirical distributions).

For the higher-than-signal cooperators (HC), lower-than-signal cooperators (LC), and the hump-shaped cooperators (HS), we built algorithms so that the simulated agents made contributions according to the group average from last round (i.e., $ratio_{i,t}$). We used the kernel

[13] Here, we used the Gaussian smoothing function, and follow Silverman (1986) to determine the bandwidth.

density estimator (6) again to estimate the ratios' distributions for the conditional players (i.e., *HC*s, *LC*s, and *HS*s). The estimated distributions are shown in Figure S4.

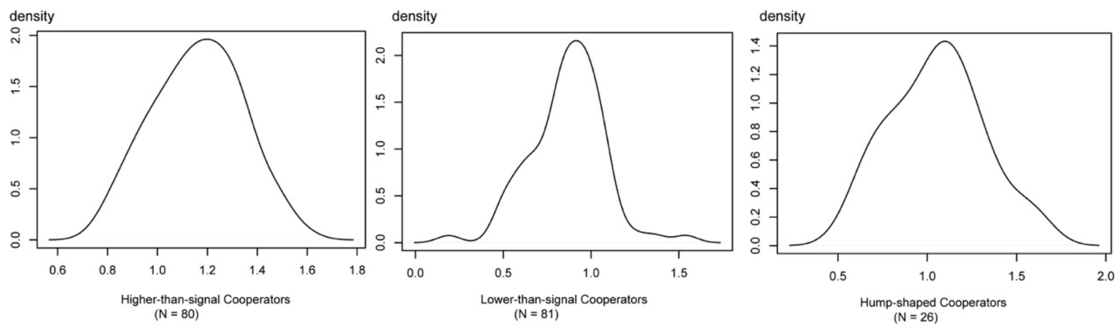

Figure S4. Distribution of Ratio for the Conditional Cooperators

For the simulated *HC*s and *LC*s, in each round, one ratio was randomly drawn from the estimated distribution. To emphasize the strategic decision rules by the *HS*, we let the simulated *HS*'s ratio changes with the signal they received. For every 10% change in signal, we estimated the ratio for *HS*s. In each round, the simulated *HS*s first determined what was the signal level in that round, and then randomly drew an element from the corresponding ratio distribution. The conditional distribution of ratio for the *HS*s are shown in Figure S5.

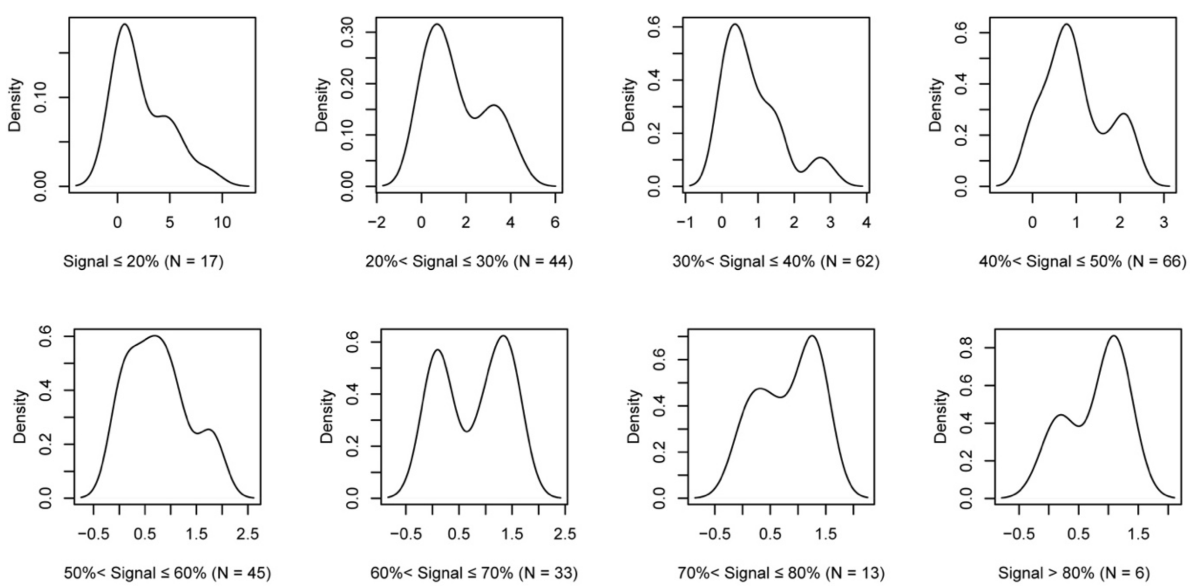

Figure S5. Conditional Distribution of Ratio for the Hump-shaped Cooperators

(3) Policy simulation

Based on evidence from the laboratory experiment, we generated a "societies" in which the population mixture was the same as in the laboratory experiment. i.e., each type of simulated players account for the same proportion as in the lab experiment. In simulation one, we first randomly drew 18 simulated players from the population and assigned them into a session. These players then make contribution decisions in round one (see the algorithm for unconditional behavior). After this decision, they receive information (signal) about the average contribution in their groups. Then the game move to round two where all the players are shuffled and reassigned into new groups. The players then make contribution decisions based on the signal they received (see the algorithm for conditional behavior). The iteration has 12 rounds. This process is exactly the same as our laboratory experiment. In simulation two, we introduced a one-instance change in the descriptive norm at the end of round one. i.e., we double the average contribution in each group and then send the modified signal to the players[14]. All other settings are the same as in simulation one.

S5. Experimental Instruction and quiz

(Translated into English. Original version is available upon request)

Experimental Instruction

Welcome to the decision-making lab of the Jianghan University of China. You will participate in an interesting decision-making experiment. The purpose of this experiment is to study how people make decisions in a social interactive situation. The experiment will be conducted on computer-based materials. Just for showing up, you have earned 5RMB. All earnings for today's tasks will be in addition to the 5RMB. You will earn "Points" through the experiment. At the conclusion of the experiment, you will be paid 1RMB for every 100 points you earned. If you pay attention and make good decisions, you may earn a considerable amount of money. The more points you earn the more monetary payment you can get. At the end of the experiment, you will be paid your

[14] One can imagine this policy as a one-time government investment that matches the total fund raised from individual firms. However, we should note that what is being modified here is the "social perception", rather than a lump-sum payment. There are many possible ways to double the perceived social norm. For example, the policy maker can also send a signal that most people are willing to cooperate by present past history.

earnings privately and in cash. You will not be paid if you leave before you conclude the experiment. We guarantee that we will treat your decisions/answers with the utmost confidentiality. For the remainder of this experiment, please refrain from any communication with other participants. Please put away your cell phones.

In the first part of the experiment, we will simulate a scenario where you need to decide how to allocate your time on two different jobs. During the experiment, every six participants will be assigned into one group to interact with each other.

Suppose you have two week-end time jobs. You can freely determine how to allocate your time between the two jobs. However, you only have 10 hours in total to work. You need to work independently on Job 1, and collaborate with other group members on Job 2.

The Decision you will make is how to allocate the 10 hours between these two Jobs.

- Job 1 (independent project) pays you 20 game points per hour.
- Job 2(group project)'s payoffs depend on the aggregate working time of all group members. Every hour spend on this project generates 40 game points. The game points from Job 2 will be EQUALLY distributed to all group members.

For example, in a group with six people, three group members devoted 5 hours on Job 2, one group member devoted 10 hours on Job 2, and the other two group members devote 0 hour on Job 2. Then in this round, the total payoff generated from Job 2 is:

$$(3 \times 5 + 1 \times 10 + 0 \times 2) \times 40 = 1000 \text{ (game points)}$$

Every group member will receive 1000 / 6 = 188.8 game points from Job 2.

In Sum, your payoffs in each round of the experiment is given by:

$$\mathrm{A} \times 20 + \frac{\mathrm{B} \times 40}{6},$$

where A is the time you spend on Job 1, B is the aggregate time that group members spend on Job 2.

In the beginning of each round, we will shuffle all participants and reassign groups. The experiment will last AT LEAST 12 rounds. The specific length of the experiment is randomly determined by the computer. To put it in another way, the experiment could come to the end at any round after the 12^{th} round.

How you will be paid:
At the conclusion of the experiment, four rounds will be randomly selected to determine you payment.

<u>Please read the above question carefully, and then complete a quiz. If you correctly answered all the questions on the quiz, you will receive an addition of 200 game points.</u>

If you have any questions, please let our experimenters know. Thanks for your cooperation!

Quiz Questions

For each of the following statements, indicate if it is TRUE of FALSE

1. During the experiment, my payoff has nothing to do with other people's decision.
2. Every group member will receive the same payoffs from Job 2 (group-project).
3. Group members are fixed through the experiment.
4. The experiment will last at least 12 rounds.
5. The experiment will end at round 12 for sure.

6. Please calculate Xiao Wang's payoff in the following round:
    He spent 8 hours in Job 1, and 2 hours in Job 2.
    On average, his team members spend 7 hours on Job 2.

    Xiao Wang earns ________ Points from Job 1 (independent project);
    Xiao Wang earns ________ Points from Job 2 (group project);
    Xiao Wang's total earnings in this round are ________ Points

Reference

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