Behavioral Patterns in the frame of Collective Risks Dilemmas with Inequality

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Abstract: How the degree of inequality affects the global patterns people follow when they have to collectively mitigate the threads of air pollution is the main topic of this study. We propose an alternative method to analyse the differences in the global behavioral patterns using experimental data from the xAire citizen science project which included two frames differentiated by the unequal distribution of resources. The method has been shown useful and we found that the degree of inequality does not determine the composition of population according behavioral patterns. Moreover, more than 50% of the people based their actions on what others people's already decided in such context thus following a moody and adaptive behaviour.

I. INTRODUCTION

As society we are facing more collectives risk situations (climate change or air pollution, Core Writing Team and (eds.), 2014) which requires to understand the way people acts in order to design the most efficient policies to reduce such risks. In this study we analyse data obtained from a lab-in-the-field public experiment, designed to generate a tension at people which have to decide between contributing in a common fond to reduce the consequences of the air pollution, or keeping the money by themselves and leaving the rest of the group paying the cost and contributing over the fair (Milinski et al., 2008).

The experiment reproduces inequality by giving an unequal distribution of resources at the beginning of the game. We understand that all monetary decisions are always done in a frame of inequality and it determines the way individuals behave (Burton-Chellew, May, and West, 2013). Analyse how decisions change according the degree of inequality is the final objective of this study.

We expect that the decisions of people are also conditioned by the decisions that others take (Fischbacher, Gächter, and Fehr, 2001). We will be able to capture the degree at which people reacts to the previous decisions which allows to understand the interactions between the individual and the group as a particle in a thermal bath.

We think that our conclusions are especially useful to policy-makers as it allows them to better understand the context of dealing with social risks that requires of a collective effort.

In terms of the literature related with the collective action we must mention the work of Fischbacher, Gächter, and Fehr, 2001 where the authors used a single shot Public Goods Game (PGG) to identify a particular group of behavioral patterns by asking to the participants of the experiment how much they were willing to contribute to a common fond according the contributions of the rest of hypothetical participants. They found that 50% of people behave as a "conditional cooperator" and 30% as a "free-rider". The rest were "altruists" (contributes unconditionally), "hump-shape" type (conditionally cooperative since a certain threshold where players start to reduce their contributions), and the "unclassified category "various".

The behavioral analysis has a long tradition with many papers reviewing the work of Fischbacher, Gächter, and Fehr, 2001. However, we have been particularly inspired by two papers Fallucchi et al., 2017 and Fallucchi et al., 2018 where the authors first redefine the classic strategies of free-rider, altruist, hump-shape, conditional cooperator and various by own maximizer (OM), unconditional cooperator (UC), strong and weak conditional cooperator (SCC and WCC), and mid-range or various (V). And second, they found the same patterns using the hierarchical clustering method which reinforces their behavioral classification. We are going to go deep through this new classification in this study.

Such behavioral studies have been done in the frame of the traditional Public Goods Game (PGG) defined in the frame of game theory. In recent years some researchers have adapted the PGG to simulate in a more proper way problems related with what is called a Collective-Risk Dilemma (CRD). A CRD experiment consists in a group of people having to solve, together, a risk by attaching a certain monetary goal through contributions along T rounds. If they do not success in this task they lose everything they have earned. The individuals in the CRD do not know a priori which strategy can be the best one to finally keep the maximum profit.

The benchmark in terms of the experimental design of the CRD was provided by Milinski and coauthors (Milinski et al., 2008). They proposed a ten shots game where groups of six individuals had to decide how many tokens wanted to contribute to a common fund at each round. They introduced inequality in their experiment modifying the initial endowment distribution and the loss rate in case of not fulfilling the objective. They found that games with a high loss rate performs better in terms of success rate (games succeeding in fulfilling the objective over the total number of games) and at same time less people played free rider strategies.

Other studies as Tavoni et al., 2011, Burton-Chellew, May, and West, 2013 and Waichman et al., 2018 have also tried to answer the same question, that is, which context (heterogeneous or homogeneous) is better to fulfill common objectives in a collective dilemma? The results provided in the literature give two opposite answers. The first one is that homogeneous games (situations were all participants have equal initial endowment) has a higher success rate than the heterogeneous games. Tavoni et al., 2011 and Burton-Chellew, May, and West, 2013 coincide with this result. However, other studies as Milinski et al., 2008 and Waichman et al., 2018 defend that heterogeneities can gives better results in terms of success rate and cooperation in the games.

II. MATHEMATICAL FORMALISM

The mathematical formalism behind the CRD is explained in detail at Waichman et al., 2018. Let's review the formalism for heterogeneous games (endowment inequality). We have n players and the game has T rounds. The contribution of each player is defined as c_{it}, that is, the contribution of subject i ($i = 1, \dots, n$) at round t. The contribution vector is build as $c_i = (c_{i1}, \dots, c_{iT})$ and the total contribution profile as $c = (c_1, \dots, c_n)$. $\tilde{c}_i = \sum_{t=1}^{t=T} c_{it}$ is the total contribution of each individual.

For the high inequality treatment (UH) two players receive 60 MU (a_H) and the rest 30 MU (a_L) (for the low inequality treatment (UL) four players receive 48 MU and 24 MU the rest). Let $j(i)$ represent the type (L or H), then utility $U_{i,j(i)}(\tilde{c})$ is the utility of player i being of type $j(i)$ under contribution profile $\tilde{c}$. In this case we can asume that to succeed in the CRD, on average half of he endowment will be spent by all players.

We use p to denote the probability of a loss occurring if total contributions fall short of a particular threshold $A \equiv \frac{n/2}{2}(a_L + a_H)$, and q to denote the loss rate of the subjects' final wealth if a catastrophe occurs.

The utility $U(a_{j(i)}$ then is defined:

$$U(a_{j(i)} - \tilde{c}_i) \text{ if } \sum_{i=1}^{n} \tilde{c}_i \geq A \equiv \frac{n/2}{2}(a_L + a_H) \quad (1)$$

$$(1-p)U(a_j - \tilde{c}_i) + pU((1-q)(a_j - \tilde{c}_i)) \text{ if } \sum_{i=1}^{n} \tilde{c}_i < A \quad ,(2)$$

In this case, the non contribution equilibrium holds. The utility is given by:

$$U_{i,j(i)}(0, \dots, 0) = (1-p)U(a_{j(i)}) + pU((1-q)a_{j(i)})$$

The catastrophe prevention equilibrium has a profile c^* that holds for the following equations:

$$0 < c^*_{it} \leq \frac{a_{j(i)}}{T} \quad (3)$$

$$\sum_{t=1}^{n} \tilde{c}^*_t = \frac{n}{6}(2a_L + a_H) \equiv A \quad (4)$$

$$U(a_{j(i)} - \tilde{c}^*_t) \geq (1-p)U(a_{j(i)}) + pU((1-q)a_{j(i)}) \quad (5)$$

This would be in schematic terms the mathematical oriented approach behind the experiments we are analysing.

III. METHODS

The experimental data used in this study was gathered from two CRD experiments organized by the UB Physics group OpenSystems one done at park Ciutadella the and the other at CCCB, both done between April and June of 2018 in Barcelona. From the CCCB we have 23 games (138 participants) and 42 (252 participants) from Ciutadella (the data cleaning process is provided in Appendix).

Our objective is to detect the change in the composition of population in terms of global behaviors when the degree of inequality is modified. To do so we are not going to focus only on the statistical differences among the macro variables of the game (proportional distribution, total contribution distribution, ...) as it is mostly done in the literature related with the CRD. But we are going to classify all participants in one of the five categories defined by Fallucchi et al., 2017 and we will compare the relative volumes of people classified at each strategy in the UH and UL treatments.

The specific strategies we are going to look for are: a) strong conditional cooperator (SCC), that is a players who matches in most of the game the average contribution made by the other players in the round before. b) weak conditional cooperator (WCC) which matches half of the time the average contribution of the players the round before. The other behavioral patterns are c) the own maximizer (OM), that is, a person which does not contribute most of the time expecting to maximize their earnings, and d) the unconditional cooperator (UC) which is the one that contributes the maximum most of the rounds independently of what others do. If a pattern does not fit to any of the last four we classify them as d) mid range or various (V).

To classify participants we propose the use of two indices which will capture the responsive behavior to others contributions and the level of altruism they show along the game. The first one is the Pearson Correlation (PC) between two series, the contribution at round t and the average contribution per game for all participants at round t - 1. The PC have a range from -1 to 1 which in terms of cooperation would mean that people is a conditional cooperator when PC is close to 1, a conditional defective if PC is negative, and a non conditional cooperator if the PC rounds 0. In our experiment only a 7.9% of the sample has negative PC and 71% of them fall in the rage (-1/3, 0) which are the non cooperators. So, to simplify the analysis we decided to do the absolute value of the PC index to keep the range between 0 and 1. On the other side there is what we define as the Contribution Index (CI) which is the average contribution per round and of each individual before the objective is fulfilled over 4 which is the maximum possible contribution people can do. In this way we have an index which also goes from 0 to 1. The combination of both indices in ranges allows to classify people in one of the five strategies we have mentioned (SCC, WCC, OM, UC and MG).

Once all participants are assigned in one of the behavioral groups we can test the statistical differences of our classification across treatments. The results of such test will say if the degree of inequality has an impact or not to the behavioral patterns people follow. The test we used is the Mann–Whitney test (as in Waichman et al., 2018) which precisely allows to compare the frequency distribution of strategies we have for each treatment.

To check our classification we review the statistical differences (also using the Mann–Whitney test) in the proportional contribution distribution among strategies, the evolution of the average normalized contribution per strategy with the standard error and finally the relation between strategies and the initial endowment. This methodology tries to give alternatives to the unsupervised cluster analysis used in behavioral experiments. When you let people interact in more than two rounds the amount of noise increase and clustering methods tend to perform less accurate.

IV. RESULTS

The first step is to classify players according to the categories defined in the last section. We computed the PC and the CI for each player and then we cross both indices in the heatmap of Figure 1. The division in ranges allows us to identify individuals that behave similarly in terms of their cooperation and contribution patterns. The amount of ranges was decided based on the best characterization of the resulting groups.

Then, we did the classification of players according to their propensity to conditionally cooperate and their degree of contribution. To do so we assign each box plotted in the heatmap to a particular behavior. The classification by ranges follows the rules defined in the Table I.

	OM	SCC	WCC	UC	MR
PC	[0, 1]	(2/3, 1]	(1/3, 2/3]	[0, 2/3]	[0,1/3]
CI	[0, 1/3]	(1/3, 1]	(1/3, 2/3]	(2/3, 1]	(1/3, 2/3]

TABLE I: Assignation of each player to a behavior according the ranges of the Pearson correlation coefficient and the Contribution Index.

This classification does not take into account the intersections between strategies. For example we could consider the people which has a PC bigger than 2/3 and a CI bigger than 2/3 as SCC-UC which would be a new strategy itself (there are 60 players which would be classified as such). To reduce the complexity of the behavioral analysis we reduce the classification to the one defined before. The results in terms of % of individuals which play mostly the same strategy are summarized in Table II.

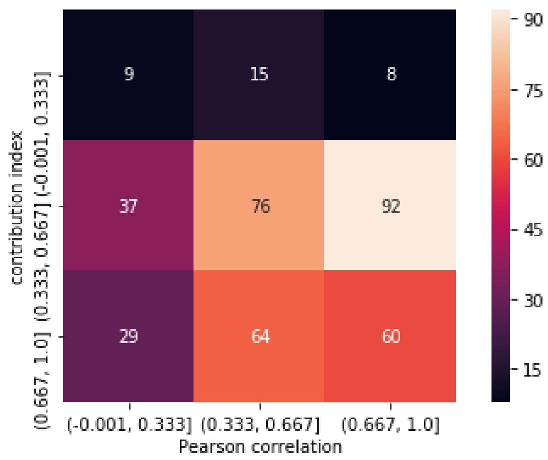

FIG. 1: Heatmap with the relation between the Pearson correlation coefficient and the contribution index in ranges.

	global	UH	UL
OM	10.0 %	9.8 %	10.4 %
SCC	38.7 %	41.1 %	34.7 %
WCC	19.7 %	17.1 %	24.3 %
UC	22.3 %	24.0 %	19.4 %
MR	9.2 %	8.1 %	11.1 %

TABLE II: % of players classified at each strategy.

Now we can see if both treatments determines the distribution of individuals across the different strategies. The results of the Mann-Whitney rank test for the two distributions of the frequency is: statistic=7.0 and pvalue=0.1481349, which implies that we can not discard the null hypothesis that both populations are equal. This result implies that we can not differentiate between the UH and the UL treatment so we will use all participants for the following analysis.

We can also compare our results with the ones found at Fallucchi et al., 2017 and Fallucchi et al., 2018, the information is summarized in table III. We can see that we have close results for the SCC, WCC and MR behavior.

Once we have the players classified in one of the five behavioral patterns then we can look for common characteristics of such groups. Actually we analyse three metrics. First, the distribution of the proportional contribution by strategy. In this case we applied first a normality test to the distributions. As only one distribution (out of five) did not fit the normal distributions then we applied the Mann-Whitney rank test. The results we found were that the populations which follow the SCC and WCC

	our results	Fallucchi2017	Fallucchi2018
OM	10.0 %	31.1 %	25.8 %
SCC	38.7 %	28.4 %	38.8 %
WCC	19.7 %	25.7 %	18.9 %
UC	22.3 %	4.0 %	4.7 %
MR	9.2 %	10.8 %	11.8 %

TABLE III: Comparison with x and y % of players classified at each strategy.

pattern can not be statistically differentiated of MR (in the case of SCC and MR the p-value was less than 10%).

Then we analysed the evolution of the averge contribution by strategy and the relation with the initial endowment. Both are basic magnitudes in the analysis of this kind of experiments. We can see the results of the evolution of the total average contribution per round (with the error-bars representing the standard error) at Figure 2.

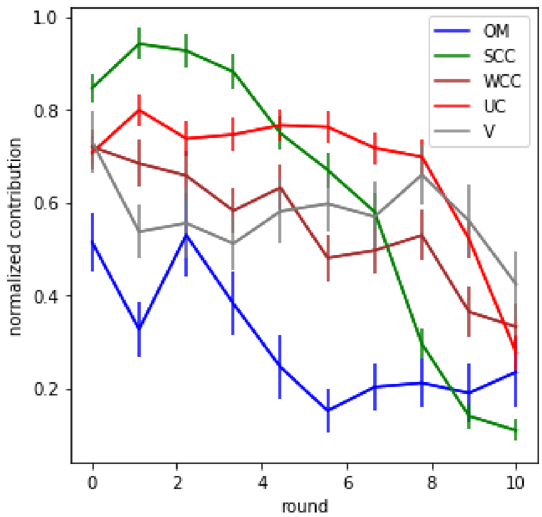

FIG. 2: Line plot with the average normalized contribution per strategy and the standard error in the errorbars.

The evolution of the contributions gives good insights about the characteristics of the patterns. For example we have checked that the conditional cooperators tend to play more strategically and contributes more at the beginning and less in the ending rounds. The weak cooperators follow the same pattern but with a smoother shape. The players categorized as Mid-Range seems to sustain their contributions along all the game regardless if the objective is fulfilled.

Figure 3 shows the relation between the initial endowment of all individuals and their assigned strategies. Strategies does not keep strong correlation with the initial endowment, although we can see that 66% of the SCC had an initial endowment of 24 or 30 MU and 70% of the people with 60 MU behaved as SCC (31%) and UC (39%).

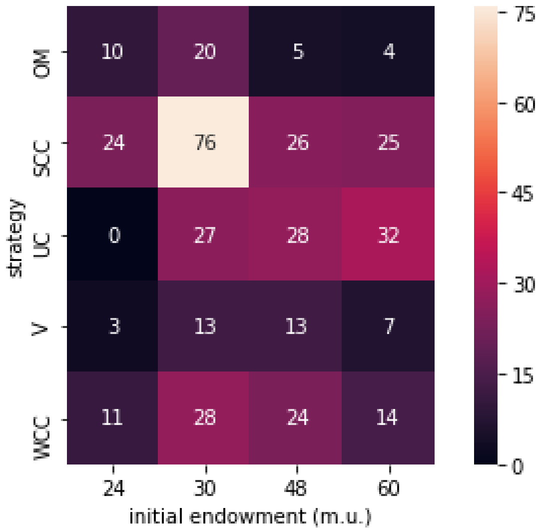

FIG. 3: Heatmap with the relation between the initial endowment and the strategy.

V. CONCLUSIONS

Participants of CRD can be classified according to their behavioral patterns. We have found that in the context of reducing the air pollution an important amount of people reacts to others' contributions (Strong Conditional Cooperator + Weak Conditional Cooperator = 58.4%) and that there are more people committed to contribute regardless of the others (Unconditional Cooperator = 22.3%) than people which tries to avoid the sacrifice and earn the maximum amount of money (Own Maximizer = 10.0%). The smallest group in terms of population is the Mid-Range with a 9.2%. Such classification is coherent with the results found in the literature (Fallucchi et al., 2017 and Fallucchi et al., 2018).

Moreover, once we classified all participants we looked at the possible statistical differences among treatments for the different proportional volumes of players in the different strategies, and we found: first, a change in the degree of inequality does not change the global behavioral patterns of people. And second, the classification results obtained does not statistically differ from the ones found in the literature. Such last finding reinforces the significance of the PC and the CI as a mechanism to characterize players associating them to a particular behavior.

To ensure that our classification is robust we reviewed three different magnitudes associated with the game as they are the proportional contribution distribution, the evolution of the normalized contributions for each strategy and the relation between the strategies and the initial endowment of participants. The statistically significant differences in the proportional contribution have and the different recognizable patterns in the evolution of the average contribution per strategy have shown a significant differentiation among the strategies which reinforced the robustness of our methods. The initial endowment has given interesting insights as it is the people with few resources (24 and 30 MU) are more sensitive to other participants contributions (behaving as conditional cooperators or own maximizers mostly) and people with a high endowment tends to contribute in a more altruistic way in the frame of the air pollution dilemma.

As a conclusion, in this study we have applied a new methodology which has been successful in clarifying the patterns associated to particular behaviors, only using the contributions that individuals made along ten rounds. It has allowed to do a classification of all the participants facilitating the posterior analysis and comparison between treatments (that is, between different degrees of inequality). Moreover, we have shown that our methodology can be an alternative to unsupervised clustering methods (Fallucchi et al., 2018 or Vicens et al., 2018). In fact, we tried to apply K-Means and Hierarchical clustering and both methods fail in recognizing the clear patterns our methodology offers.

Many things have been left for the sake of the extension. A complementary analysis with unsupervised clustering methods, a deeper characterization of the behavior in the different periods of the game, or the inclusion of more features in the analysis (as the answers of a final questionnaire all players did) are possible topics for future research.

VI. APPENDIX

A. Data Cleaning

The first condition was to eliminate all players which did not finish the game, and the games in which those players were (3 games at CCCB dataset and 4 at Ciutadella). It was necessary to have all games with the same amount of players to be able to aggregate results. The second one was to eliminate those games which had some kind of problem with their information (2 games at Ciutadella had the total contribution equal zero according the system while players actually did contributions). The last condition was a criteria to determine outliers of the dataset. We used the total contribution distribution and we eliminate those games which fall out two standard deviations of the distribution (we dropped 2 games at Ciutadella and 3 at CCCB). The results of the normal approximation are: average total contribution = 132.2 MU, standard deviation of the total = 12.7 MU and the validity range with two sd = [106.78 MU, 157.70 MU]. We finally drop the EQUAL treatment games as they were not statistically significant to compare with the rest of treatments. At the end we have 65 games and 390 players and two treatments.

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