MODELLING THE EFFECT OF INDIVIDUAL DIFFERENCES IN PUNISHMENT SENSITIVITY ON BEHAVIOUR IN A PUBLIC GOODS GAME

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ABSTRACT
Previous research on social dilemmas demonstrated that various forms of punishment for free-riding can increase contribution levels in public goods games. The way individual group members react to the possibility of punishment can be also affected by individual differences in punishment sensitivity. Therefore, depending individual differences in punishment sensitivity of group members, different levels of punishment can be more or less effective to prevent free riding behaviour. This paper uses agent-based modelling to model the effect of punishment sensitivity on contribution levels in a public goods game. The paper then examines the correlation between punishment sensitivity and variability of free riding behaviour under different punishment conditions.

Keywords: agent-based modelling and simulation, behavioural game theory, public goods game, punishment

1. INTRODUCTION

Public Goods (PG) game is a standard experimental economics approach to study human cooperation. In this game each player faces a dilemma: to invest into PG and potentially get a higher return through cooperation in the future; or keep their endowment which essentially means free riding on other people's contributions. A standard finding using this paradigm is that there is variability in behaviour: some individuals cooperate while others free-ride (Fehr & Gächter 2002; Fischbacher et al. 2001). Since cooperation is a fundamental feature of human society, it is important to understand why people choose to free-ride, and what factors can decrease levels of free-riding. One mechanism to promote cooperation is monetary punishment for free riding. Previous research demonstrated that the way people are affected by the punishment in the PG game differs between individuals and the differences are explained by trait punishment sensitivity (Skatova & Ferguson 2013). In their experiment, participants played a series of standard PG game with varying punishment conditions. Individual punishment sensitivity of participants was assessed through Behavioural Inhibition Scale (BIS, Carver & White 1994). The results demonstrated that participants contribute more under threats of punishment compared to no threat of punishment, and that people with higher punishment sensitivity provide higher contributions (free ride less) even when punishment is not certain. This research suggests that varying probability of punishment could affect contribution levels of groups depending on individuals' levels of punishment sensitivity. However, the lab-based design of experiment with real participants limits opportunities to test how different levels of punishment threat in combination with different levels of sensitivity to punishment of group members, affects contribution levels of different groups. Current paper aims to fill this gap by modelling an experimental game using agent-based modelling and simulation. This will allow to capture group dynamic through varying parameters of punishment and sensitivity to punishment in a series of artificial experiments.

2. BACKGROUND

2.1. Public Goods Game and Punishment

In experimental economic, a laboratory PG experiment consists many participants, which are matched into groups (usually of four people). They will have an endowment of Money Unit (MUs) which they can keep for themselves or invest into a public account. The invested money is multiplied and distributed equally to all group members. This creates a dilemma: by investing something into PG, the player loses this money from their private account but potentially gains from future profits from public account. However, if the player contributed more than others, they will be worse off in the end, as the profits are distributed equally. Those who contribute less than there group members, therefore, free ride on the public good. Many researches attempted to explain the reason behind free-riding and how to maintain cooperation. One of the central mechanisms to sustain punishment in large groups is punishment. For example, Guillen et al. (2007) showed that central authority punishment increases the contribution comparing to the standard game.

2.2. Agent-based Modelling and Simulation

Agent-based Modelling and Simulation (ABMS) is a methodology that has been utilised recently by social scientists and economists to model social system. ABMS is individual-centric and decentralized approach, in which a system is modelled using fine-grained models with attention to dynamics. In economics, economies are complex dynamic systems, which are composed of many interacting units (individuals, organizations) and exhibit emergent properties. With ABMS, economic systems can be modelled from the bottom up, considering the global behaviours rooted in the local interactions (Tesfatsion 2006).

Agent-based Modelling and Simulation is suitable to model the PG game experiment, because the experiment is a human-centric system and an agent represents a human very well. An agent, same as a human, is heterogeneous (with its own goals, behaviours), autonomous (can adapt and modify their behaviour), and proactive (adjust action depending on internal state) (Wooldridge & Jennings 1995).

3. METHODOLOGY

3.1. The public goods game

The simulated game will be in the same format as the experiment of Skatova & Ferguson (2013). The game comprised four blocks with punishment conditions in the following order:

1. A non-punishment block (standard PG game)
2. A implemented punishment block
3. A non-implemented punishment block
4. A non-punishment block

Each block consisted of 10 trials (rounds). After each trial, participants were shuffled and put into group of four players they did not play before with. Each participant received the initial endowment of 20 MUs, which could be divided to the private and public account. After everyone made their investment decision, the payoff then calculated based on the following function:

$$\pi_i = 20 - g_i + 0.5 \sum_{j=1}^{4} g_j \qquad (1)$$

Where a pay-off (π) for a participant i is defined by their contribution (g) and the sum of contributions of other players in the group.

After the first block of a standard PG game, participants received additional instructions for the next three blocks, which introduced a punishment rule. In the non-implemented punishment block, the punishment never occurred. In the implemented punishment block, the punishment actually occurred in two out of 10 trials.

3.2. The agent-based model

The agent-based model is implemented in AnyLogic 7, (XJ Technologies 2015), a multi-method simulation modelling tool. In the model, agents representing the participants played a series of one-shot PG games with three different conditions: non-punishment, implemented and non-implemented punishment.

There were two types of agents: Main and Person. There was one Main agent, which acted as a game master, controled the game stage, and let Person agents know about the stage, and punishment condition of the game. There could be many Person agents, which represented the participants in the game. At the beginning of each game, each Person agent was assigned to a Group, which was implemented using a Java class. Group object managed the contribution and punishment of the group.

The behaviour of agents was modelled using statechart. Statechart diagrams described different states of an agent and the transitions between them, and could be used to visualize and model the reaction of agents by internal or external factors. The use of statechart to model agent behaviour is described in the sections 3.2.2 and 3.2.3.

3.2.1. Strategies of Person agents

For every Person, there was a variable: *Punishment_Sensitivity*, which represented punishment sensitivity value measured by BIS-anxiety score, a subscale of BIS (Skatova & Ferguson, 2013). *Punishment_Sensitivity* ranged from 1 to 4. Based on Skatova & Ferguson's work, there were differences in behaviours of people with high and low punishment sensitivity. Accordingly, we categorized Person agents based on its *Punishment_Sensitivity* variable. The agent were categorized as "high-anxiety" if *Punishment_Sensitivity* of a Person agent was greater than 3.13. Person agents with *Punishment_Sensitivity* less than 3.13 were "low-anxiety". People with different anxiety had the tendency to use different strategies. There were five available strategies for Person agents:

1. **Full Cooperation (FC)**: always contributed 20 MUs.
2. **Strong Conditional Cooperation (SCC)**: contributed 3-4 MUs more than average group investment in previous round.
3. **Normal Conditional Cooperation (NCC)**: contributed the same or difference of 1 MU with average group investment in previous round.
4. **Weak Conditional Cooperation (WCC)**: contributed 3-4 MUs less than average group investment in previous round.
5. **Full Defection (FD)**: always contributed 0 MU.

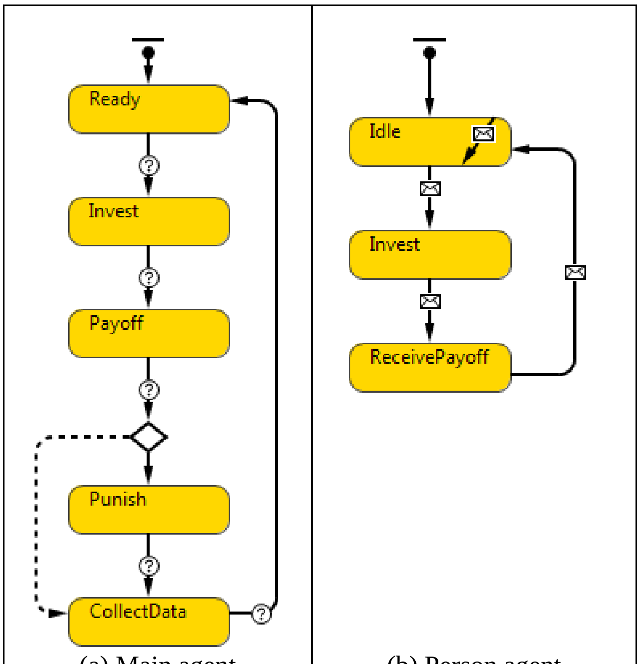
High-anxiety agents tended to contribute more; while low-anxiety agents tended to contribute less. Therefore, at the beginning, each Person agent was assigned with a strategy and a *Punishment_Sensitivity* value following the distribution in Table 1.

Table 1: Person agent initialization

Percentage of agents	**Strategy**	**Anxiety**
5%	FC	100% High
20%	SCC	80% High, 20% Low
50%	NCC	50% High, 50% Low
15%	WCC	20% High, 80% Low
10%	FD	100% Low

3.2.2. Modelling game play

The Main agent and Person agents used two statecharts (Figure 1) to coordinate and play the game. The game had several stages such as invest, payoff, punish. Each stage of the game was represented by a state in statechart of the Main agent. Based on the current state of the statechart, the Main agent sent messages to all Person agents to inform the current stage of the game. Based on the received message, the Person agents also made transition to the corresponding state.



(a) Main agent (b) Person agent

Figure 1: Gameplay statecharts of Main agent and Person agent

At the beginning, when in "Ready" state, the Main agent prepared for the game by setting up variables, shuffling Person agents, and assigning them to groups. Then the Main agent changed state to "Invest", in which messages were sent to all Person agents. Person agents were in "Idle" state would change to "Invest" state when they received the message, and made a decision on how much to invest based on their strategy. After all Person agents made investment decision, the Main agent went to "Payoff" state and sent messages to all Person agents. The Person agents changed to "ReceivePayoff" and asked the Group object to calculate the payoff and the average investment of the group. After receiving payoff, Person agents went to "Idle" state. In the Main agents, if punishment was implemented during that game round, Person agents went to "Punish" state, and sent messages to Person agents. There was a self-transition in "Idle" state of Person agents, which was triggered when they received message about punishment. When triggered, Person agents asked Group object whether they got punished. If punishment was not implemented, Main agent changed state from "Payoff" to "CollectData", and then went back to "Ready" state.

3.2.3. Modelling individual differences in punishment sensitivity

A representation of Punishment Sensitivity was implemented in each Person agent to represent individual differences related to BIS-anxiety value. People with higher punishment sensitivity would be more cautious and avoid free-riding behaviour in response to signals of punishment. In addition, people were only cautious for a period of time and then they forget about punihsment. Therefore, the agents were contributing more when there was threat of punishment, and only being cautious for several rounds after. The behaviours were modelled with a statechart (Figure 2), which had two states: "Normal" and "Cautious". The state change was controlled by two transitions:

- From "Normal" to "Cautious": This transition was triggered if (the agent was high-anxiety AND there was threat of punishment AND the agent had not been in cautious state) OR (the agent got punished).
- From "Cautious" to "Normal": This transition was triggered if (there was no threat of punishment) OR (a low-anxiety agent had been in "Cautious" state for 3 rounds) OR (a high-anxiety agent had been in "Cautious" state for 10 rounds).

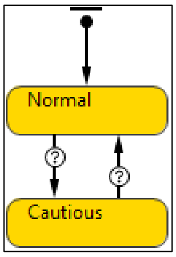


Figure 2: Punishment Sensitivity statechart of Person agent

Table 2: Strategy change of Conditional Cooperators

High Anxiety	
Normal to Cautious	$SCC \xleftarrow{0.2} NCC \xleftarrow{0.8} WCC$; $NCC \xrightarrow{0.8} NCC$; $WCC \xrightarrow{0.2} SCC$
Cautious to Normal	$SCC \xrightarrow{0.2} NCC \xrightarrow{0.2} WCC$; $SCC \xrightarrow{0.8} SCC$; $NCC \xrightarrow{0.8} NCC$
Low Anxiety	
Normal to Cautious	$SCC \xleftarrow{1} NCC \xleftarrow{1} WCC$
Cautious to Normal	$SCC \xrightarrow{0.8} NCC \xrightarrow{0.8} WCC$; $NCC \xrightarrow{0.2} NCC$; $SCC \xrightarrow{0.2} WCC$

When a Person agent changed state, the strategy of that agent would also be changed as well. The high-anxiety agent using FC strategy did not change strategy. The low-anxiety agent using FD strategy would change to WCC strategy when changing to "Cautious" state, and change back to FD strategy when changing to "Normal" state. For the agent who was using conditional cooperation strategies (SCC, NCC and WCC), the strategy change followed as described in the Table 2. When changing to "Cautious" state, agents would avoid free riding and stop using WCC strategy. Because agents with high anxiety contribute more under threat of punishment, when agents changed to "Cautious" state, high-anxiety agents were more likely to change to SCC than low-anxiety ones. For example, in the first graph of Table 2, 80% of high-anxiety agents using WCC strategy changed to NCC strategy, and the rest (20%) changed to SCC strategy. When agents changed to the "Normal" state, low-anxiety agents were more likely to use WCC strategy than the high-anxiety ones.

4. EXPERIMENTS AND RESULTS

4.1. Validation Experiment

In this experiment, the model was set up with the similar settings to Skatova & Ferguson (2013) to validate the simulation results and examine whether the model replicates the contribution level over different blocks as well as the correlation between punishment sensitivity and free riding behaviour of a real experiment. The simulation was set up with 1000 Person agents, initialized with different punishment sensitivity value and strategy based on Table 1. Person agents played four blocks (10 trials each block):

1. A non-punishment block
2. A implemented punishment block
3. A non-implemented punishment block
4. A non-punishment block

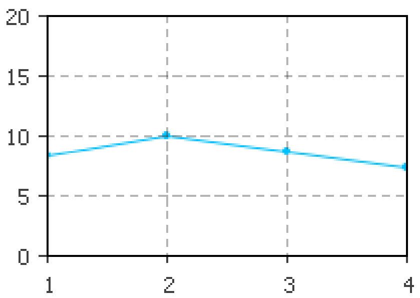


Figure 3: Average investment over four blocks

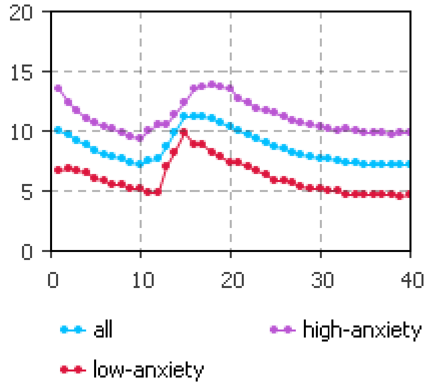


Figure 4: Average investment over 40 trials

Only the Main agent knew about the punishment conditions of the blocks. The Main agent just informed Person agents that there would be a threat of punishment in the second and third block. In the implemented punishment block, punishment was implemented in two out of ten trials.

The average group investments over four blocks, showed in Figure 3, replicated the trend in Skatova & Ferguson laboratory experiment. The average investment in the first block of standard PGG was 8.25. In the second block where punishment was implemented in two out of ten trials, the group investment increased to 9.77. In the third block where the punishment was expected but not implemented, the group investment decreased to 8.64. In the last block of standard PGG, the group investment dropped to 7.34.

In the second block of this particular experiment, the punishment was implemented at block 12 and 14. Figure 4 shows that the average investment had a sharp rise after block 12 and 14. In those two trials, it appeared that free-riding agents, especially low-anxiety agents, got punished, switched to more cooperative strategies, and contributed more in the next ground. If this was a lab experiment, we would not be able to investigate much further. But since we used an agent-based model, we could analyse the decision making process of agents better.

Figure 5 shows the states of punishment sensitivity statechart of all agents. In the first 10 rounds, all agents were in "Normal" state. When there was a threat of punishment, high-anxiety agents changed to "Cautious" state. In block 12 and 14, when the punishment was implemented, free-riding agents got punished and changed to "Cautious" state. The more agents were in "Cautions" state, the more contribution there was overall. The strategy change of conditional cooperators, who were the majority, played a crucial role to the contribution in the system. Figure 6 and 7 shows the strategy change of high and low anxiety agents. High-anxiety agents changed to more cooperative strategy when there was a threat of punishment then changed the strategy again after being cautious for 10 rounds. Low-anxiety agents still used the same strategy even when there was a threat of punishment. They only changed when punishment was implemented (trial 12 and 14): the more agents used SCC, the less agents used WCC. After 3 rounds of being cautious, low-anxiety agents changed back to Normal state, and used less cooperative strategies.

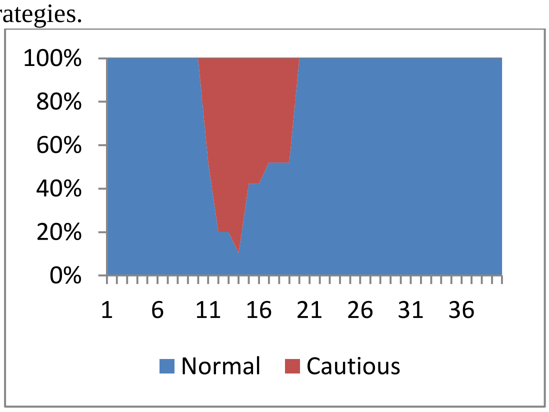


Figure 5: Agent states of punishment sensitivity statechart

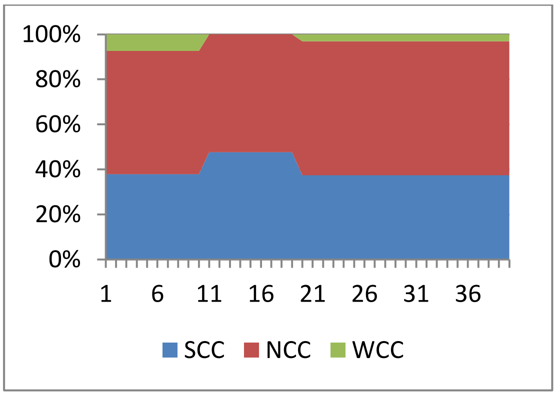


Figure 6: Strategy of high-anxiety agents

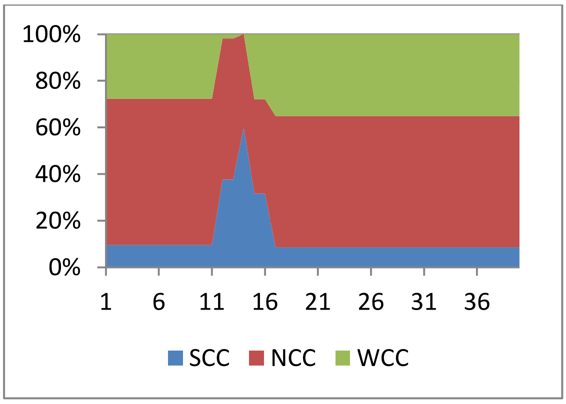


Figure 7: Strategy of low-anxiety agents

4.2. Experiments with different Punishment Conditions

One of the applications of this model is to use it for examination of the contribution levels under different levels of punishment. In this experiment, the model was set up with the same ratio of agents but under different punishment conditions. We then analysed the simulation results to understand more about free-riding behaviours in various punishment conditions.

Figure 8 shows an experiment where in every trial punishment was expected but only implemented periodically. If the punishment was implemented every trial, the contribution level increased gradually before stabilizing. The same trend occurred for implemented punishment every 3 trials, but the contribution level was lower. If the punishment was implemented every 5, 10 or 15 trials, the contribution levels oscillate, which meant contributions decreased over time and only increased in trials with implemented punishment. The greater the period between two implemented punishment trials, the lower was the contribution level.

Figure 9 and 10 show another experiment in which agents played in a series of non-punishment blocks of PG games, and the implemented punishment blocks occurred periodically. In the implemented punishment blocks of Figure 9, randomly on *two out of ten trials* individuals were punished. While in Figure 10, randomly on *five out of ten trials* punishment was implemented. The contribution level decreased and for certain number of trials became stable, to only increase when punishment was implemented. Comparing between Figure 9 and 10, the contribution level (overall as well as the peaks) was higher in Figure 10. This was because there were more trials where punishment was implemented in Figure 10 than in Figure 9.

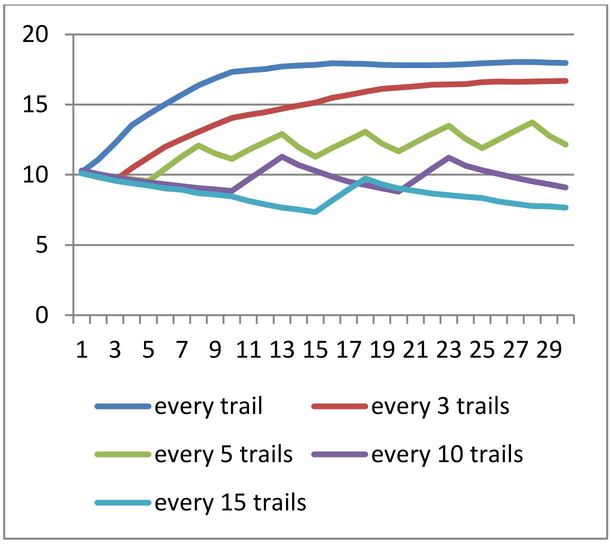


Figure 8: Punishment was periodically implemented on trials in an expected punishment condition

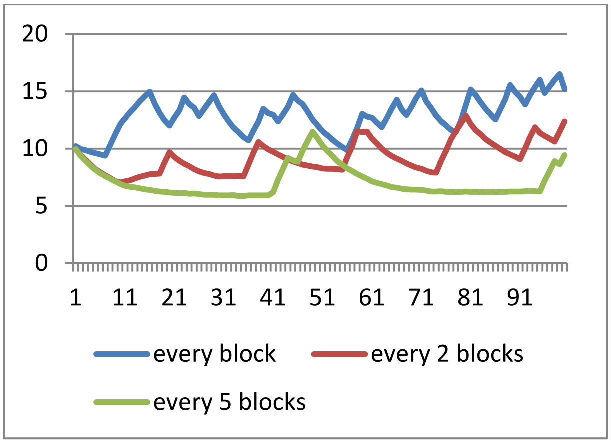


Figure 9: Punishment was periodically implemented in a block with *two out of ten* punishment games per block

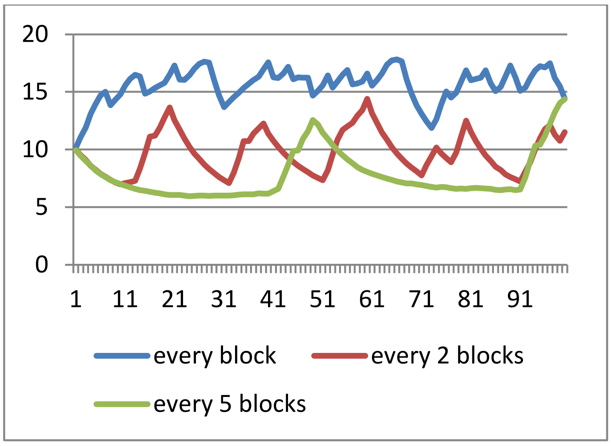


Figure 10: Punishment was periodically implemented in a block with *five out of ten* punishment games per block

The above experiments showed that contribution levels had different dynamic in different punishment conditions. Using the agent-based models as a decision support tools, policy maker could be able to decide on how to implement punishment in order to achieve a desired pattern of contributions in the real world public good scenario.

4.3. Experiments with different ratios of strategy

In this experiments, we investigated how the ratios of strategy used by agents are affected the total investment of four blocks. Figure 11 shows the results of six experiments. The total percentages of five strategies (FD, SCC, NCC, WCC, FD) were 100%. In all the experiments, the percentage of FC was fixed to 5%. There were three experiments with 10% of FD (solid line), and three experiments with 30% of FD (dotted line). So in each experiment, the percentages of FC, FD, and SCC were fixed, then percentage of NCC was varied from 0% to 100%, and the rest would be percentage of WCC. The percentage of NCC was represented by the x-axis, while the total invesment was represented by the y-axis. For example, the red solid line had 5% FC, 10% FD, 20% SCC; and as the percentage of NCC increased, the total investment increased as well.

How the ratios of strategy affect the total investment can be concluded by comparing between these experiments:

- Looking at one experiment, we noted the larger the percentage of NCC was, the more investment there was into PG.
- Comparing between the blue, red, green line, we saw that the larger the percentage of SCC was, the more investment there was into PG.
- Lastly, comparing between the solid line (FD 10%) and dotted line (FD 30%), the smaller the percentage FD was, the more investment there was into PG.
- With FD of 10%, the increase in percengate of SCC (from 0% to 20% to 50%) resulted in bigger raise of total invesment comparing with FD of 30%.

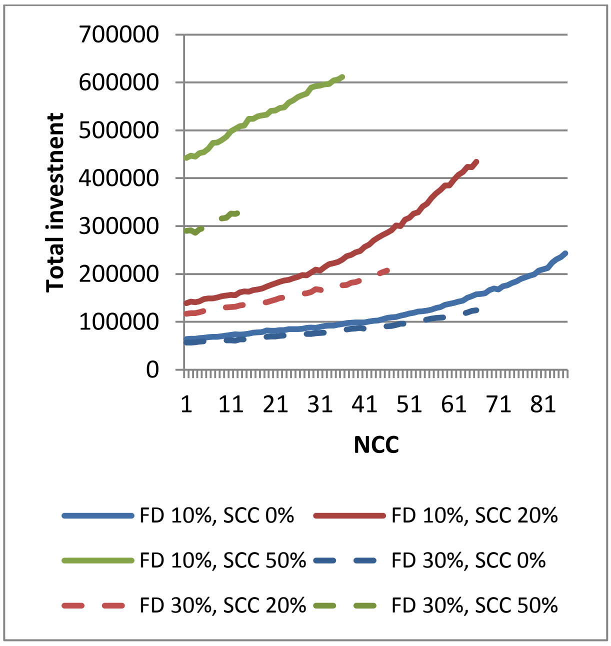


Figure 11: Total investment in different ratios of strategy

Table 3: Experiments with different ratios of anxiety

Strategy	**Anxiety**		
	Exp. 1 (baseline)	**Exp. 2**	**Exp. 3**
FC	100% High	100% High	100% High
SCC	80% High, 20% Low	*80% High, 20% Low*	*20% High, 80% Low*
NCC	50% High, 50% Low	*80% High, 20% Low*	*20% High, 80% Low*
WCC	20% High, 80% Low	*80% High, 20% Low*	*20% High, 80% Low*
FD	100% Low	100% Low	100% Low

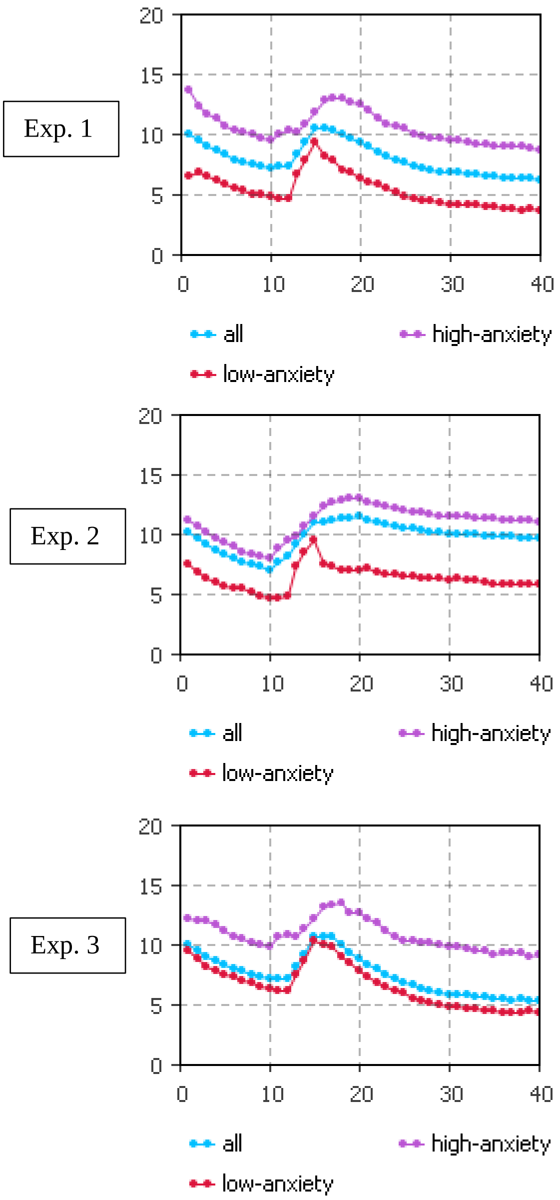


Figure 12: Investment over time in different ratios of anxiety

4.4. Experiments with different ratios of anxiety

The final experiments were to change the ratios of anxiety and examined the investment over time. Using the experiment in section 4.1 as the baseline, two more experiments were set up by changing the ratios of high and low anxiety of conditional cooperators (CSS, NCC, WCC). In the second experiment, 80% of conditional cooperators were high anxiety and 20% were low anxiety. In the third experiment, 20% of conditional cooperators were high anxiety and 80% were low anxiety. Table 3 shows the three experiments and corresponding percentages of anxiety levels.

The results of three experiments are shown in Figure 12. In the first block (first 10 trails) the investment trend was the same for the three experiments. This is because the investment in the standard PG game is only affected by the ratio of strategies used by agents, not by their anxiety.

For the last three blocks:

- In the second experiment, because there were more high-anxiety agents, the investment was increasing faster than the first experiment, and became stable at higher value.
- In the third experiment, because there were more low-anxiety agents, the investment was increasing to approximate the same value of the first experiment, but became stable at lower value.

5. CONCLUSION AND FUTURE WORK

Using agent-based modelling and simulation, this paper has modelled the effects of individual differences in punishment sensitivity in a Public Good Game. The simulation has validated the behaviours which observed in Skatova & Ferguson laboratory experiment. This agent-based model can be used as a decision support tool for policy makers to examine the free riding behaviours in varying punishment conditions in a real world scenario which resembles a public goods game (e.g., recycling, littering, energy use at home, etc).

This paper also demonstrated that agent-based modelling and simulation can be used to investigate different aspects of human decision-making which do not integrate with traditional economic models of behaviour. Researchers have been trying to extend the traditional approach by integrating other sciences (such as psychology and neuroscience) to add more layers into human decision-making models. Theoretical models can be validated by using the approach developed in this paper. Modeller can build an agent-based model in which the overall decision making process of agent is affected by the combination of many decision-making factors derived from models in different disciplines.

In future research, classification techniques can be used for analysing the change in the strategy of participants in the laboratory experiment with different punishment conditions, and developing a method to capture the change in contribution levels. It is also interesting to collect more data on the interaction between strategies and anxiety of people from different demographic groups.

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