Prisoner's Dilemma on a Network with Communication

Agent Based Modelling Assignment at UvA

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1 INTRODUCTION

Over the past few decades, internet has become a crucial part of everyday life [1]. Among other things, it is used to connect people and share content like videos and photos, but also educational information. In the previous year, we have witnessed the internet becoming a crucial element to make it through the COVID-19 pandemic, as it allowed for work and study to be conducted from home.

However, we have also seen that the power of the internet can be abused for malicious practices, such as spreading fake news [2]. This can have a great impact on society as the opinion of the crowds can be altered to influence public events, such as elections and protests. The power social influence can have over the perception of facts is also evident by the fact that groups such as *'Flat Earthers'* are on the rise. The price of these influences can be high, as we have seen with riots against the implementation of COVID-19 measures or fair elective system happening throughout the world recently. Anti-vaccination ideology, built solely on false information spread through social media, puts at risk the health of the ideologist and society as a whole.

The wisdom of a crowd is determined by the level of social influence as well as other parameters such as diversity and independence of opinion [3]. Social influence is described as the effect choices and opinions of other people (friends or colleagues) have on the decisions of an individual. [3] mentions that the effect of social influence strongly depends on the starting conditions.

This paper aims to view the effect of social influence on the strategies played by agents spread over a real-world network in a Prisoner's Dilemma game.

The Prisoner's Dilemma is a well-known topic in the field of Game Theory. It is described with two criminals called in for questioning by a police officer who knows of their crime but does not have enough evidence to charge them for it. The criminals are put into separate rooms, so no arrangement between them can be made whether to admit or keep quiet. The offer is as follows: *'The full sentence for the crime they have committed is 5 years. If both of the criminals admit to the crime, they will be charged with a looser sentence of 4 years each. If one of the criminals admits while the other stays quiet, the one admitting will be set free with no punishment, but his partner will suffer the full sentence of 5 years. However, if both of the criminals stay quiet, they will both be free after only 2 years in prison.'*. From now on, the criminal admitting the crime will be referred to as defecting, D, (risking that partner might suffer the full sentence so he could get the highest payoff) and the act of keeping quiet as cooperating, C, (not putting any risk on the partner). The payoff here is referring to the number of years criminal's sentence has been lowered from the full sentence. This yields the following payoff matrix showing the payoff of the criminals for all possible combinations of 'strategies' (C/D): Table 1.

Table 1: Prisoner's dilemma game, payoff matrix.

	C	D
C	(3,3)	(0,5)
D	(5,0)	(1,1)

In the case described above, where the criminals will only find themselves in this situation once and where their choice of action is in no way influencing the action of the other player(s), there is a single best strategy that a rational, fully selfish player should choose and that is to defect. In case the other player chooses to defect, the payoff for the first player if he defects is higher (1) than if he cooperates (0). In case the other player cooperates, the first player will still gain a higher payoff (5) if he defects than if he cooperates (3). For this reason, in a single Prisoner's dilemma game played by fully rational and selfish players, one can always expect both players to defect.

This, however, no longer holds if multiple rounds of the game are played (a match), players are responsive to the outcomes of the previous rounds and they play the game against multiple opponents with their score being the average of scores gained in all of the played matches. Given these presumptions, there has yet to be found a single best strategy a player should play in a match. This is due to the fact that the outcome is very much determined by the opponents a player is playing against. However, overall, the winning strategies have been found to initially cooperate in this research [4] despite the risk of losing against a defector. In the first tournament organized by Axelrod [4], it was found that all of the top-performing strategies are ones that will never be the first ones to defect, except maybe in the last few rounds. Another feature of the winning strategies was found to be not holding grudges (giving the opponent a second chance despite him having defected against you). The same features were found to be predominant in the case of the evolutionary Prisoner's dilemma, where players have an option to change their strategies for the ones performing better in the tournament [5].

As discussed before, it is wrong to assume humans to be fully rational creatures. The effect of social influence can be such that an agent refuses all facts and acts solely on feelings. In the aim to perform better, due to his clouded perception, one might choose a strategy that will actually give him a lower prize. Say this person has a great appreciation for his good friends who are not obtaining high scores in the tournament but is deeply disappointed in all of the people who are succeeding (they were in a fight or he has found out about their poor life choices). If this person often acts on his feelings (is not very rational), the high scores of 'bad' people will seem to him as less valuable than his 'beloved' friends small successes, and he will choose the worse performing strategy.

In this paper, we introduce a network-based agent-based model (ABM) where each node represents a human agent with a certain level of rationality and a position in the social hierarchy. Each timestep, they play a Prisoner's Dilemma match with a random agent and consider the outcomes of these matches, after which they possibly switch strategies. This decision is based on their level of rationality, their social ranking and the outcomes of the game. For the purpose of simulating a real-world environment, a network based on the data collected from Facebook by the team responsible for creating the SNAP library for the analysis of networks from Stanford University [6] was used.

The following questions will be answered:

- Can there be found a prevailing strategy despite the agents being under the influence of social influence or will it depend on the initial conditions?
- Will cooperation again show as the winning strategy and will it manage to prevail?
- How big of an influence will the social influence have?

2 BACKGROUND

There were three stages in developing social simulation: macro-simulation, micro-simulation and ABM[7]. A macro-simulation model ordinarily consists of a group of differential equations. The system of these differential equations can be used to predict population distribution. This model has many applicable scenarios, such as stockpile management, immigration monitoring, and viral transmission[8] [9]. Based on macro-level forecasting, individuals are analyzed as a unit by social scientists. Caldwell[10] indicated that micro-simulation is a 'bottom-up' modelling method that simulates the intercommunication between individual decision-makers in the system. Although the micro-simulation model can change elements of the distribution instead of changing the distribution at the macro level, it does not allow individuals to interact directly. Therefore, in the third stage, the ABM model is used for social simulation. Both ABM and micro-simulation are 'bottom-up', but the difference is that in an ABM individuals interact independently. Agents can generate a complex adaptive system during the interaction by e.g. moving and learning[11]. Often, these individuals are able to learn from the interactions when they are fulfilling their goal, which is always to seek utility maximization. Even if the local interaction is consistent with simple rules, the rules are not complex enough to explain the complex social impact caused by heterogeneous individuals. Hence, no model can assume that a stable equilibrium can be found[12]. Therefore applying these ABM models helps to understand the system by controlling the agent interactions[11].

There have been studies combining evolutionary games and population network models. Many subjects in this field have been studied under different circumstances, such as the robustness of population structure of prisoner's dilemma games[13], the impact of small-world network models and regular lattices on the evolutionary results[14][15] and the clustering effects on evolution games[16]. Many population networks are included when discussing the social simulation model, such as Watts-Strogatz small-world networks[17] and Barabasi-Albert scall-free networksp[18]. Although different networks have distinct topologies, population structure and distribution have no consistent impact of structure on the evolutionary games even for the same network type[19]. Therefore, this research focuses on the iterated prisoner's dilemma in an ABM using the real-world social network.

The most famous publication in IPD research is Axelrod's book: 'The Evolution of Cooperation'[5]. This book explains IPD in detail and presents the robustness of always defect strategy and Tit-for-tat(TFT) strategy from his computer tournament. It also shows how computational simulation can advance the social sciences. This paper continued with Axelrod's central idea combined with Lozano's application on real social networks[20]. We hope that based on current results and our ABM results, we can give a more intuitive explanation of IPD combined with the network model.

3 METHODS AND ODD

3.1 Purpose

Witnessing the effects of social media and social influence on the decisions made by an individual raises the question of how far a population can skew from the ideal, only due to clouded rationality. This paper focuses on the influence that social perception can have on an agent's choice regarding the strategy played in a Prisoner's dilemma match[1]. The aim of the agents is to achieve the highest payoff in a match ('to possibly lose a battle, but never the war'). Therefore he always chooses the strategy he deems the best. The agent's perception, dependant on values describing his level of rationality and rank in a social hierarchy, might lead him to poor decisions. We consider this model of clouded perception as a possibly useful model. To better understand our societies, where irrational and unprofitable ideas can still be a breakthrough.

3.2 Entities, state variables and scales

Our model consists of agents which are spread on a social network. The network is created based on the data collected from Facebook [6]. We sized the network down to 1055 nodes due to computational resource limitations. Each node represents an agent and is assigned a value between 0 and 1 describing his rationality and another value between 0 and 1 describing his rank in the social hierarchy. Both of these variables are initialised with a value from a truncated normal distribution.

[1] https://github.com/ennokuyt/ABM

Another parameter of the model is the *switch random* parameter, describing the probability that an agent will choose a random strategy from the strategy set, instead of the perceived best strategy. The default value for this parameter is 0.05. To prevent the model of converging to an optimal local distribution, switch random was added to make the model explore the solution space. The benefit of having the model explore the solution space with a certain probability is that it is more likely to converge to a global minimum, and also reducing the variance. Among people this can been seen as making a mistake. Evaluation of strategies goes according to the following equation:

$$strategy(A) = \sum_{i \in S_A} \frac{rationality * score_i + (1 - rationality) * score_i * \frac{rank_i}{rank}}{|S_A|} \quad (1)$$

where S_A is a set of "friends" (two nodes are friends if they are connected with an edge) of the agent who has played the previous match with a strategy A and *rationality* and *rank* are rationality and rank values of the agent performing an evaluation. $score_i$ represents the average score an agent has achieved in the previous match. In each round of the game, all agents are randomly assigned a pair they will be playing against in this round. A round consists of 10 Prisoner's dilemma games played against a single opponent.

The level of rationality among agents is assumed to follow the Gaussian curve [**Gauss**] and a fully rational agent is assumed to base its decisions solely on facts and not opinions. The circumstances needed for a particular strategy to prevail will be discussed.

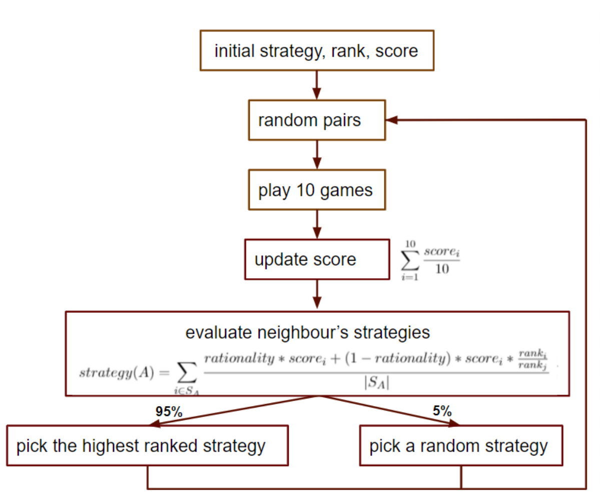

Figure 1: Schematic overview of agent. Note: the probability of picking a random strategy is 5% here, however in the real model this is an input parameter.

3.3 Process overview and scheduling

The model flowchart is shown in Figure 1. The model starts by assigning an initial strategy to each agent and setting his level of rationality and social influence (rank). At the beginning of each time step, all agents are randomly paired and they play a match of 10 games against their opponent. Their score is updated after the match and they wait for all of the other pairs to finish their games. Once all of the scores have been updated, each agent evaluates the strategies of his neighbours and makes either the best perceived or a random strategy as his new strategy. The model then proceeds to the next time step.

3.4 Design Concepts

The *Basic principles* in the model are rationality and social influence. For the implementation of the basic evolutionary prisoner's dilemma is used. In this basic model, the agents move randomly on a grid, if they encounter another agent, a prisoner's dilemma is played. The loser dies and the winner reproduces. The offspring have the same strategy as the parent agent. In our model agents do not move but are randomly paired up to play the prisoner's dilemma. Instead of reproducing and dying the agents reevaluate the strategy based on the performance, rationality and social influence of their friends. The model will show how different populations will be influenced by their connecting nodes.

Expected is the *emergence* that social influence has less effect in evaluating the strategies as the agents are more rational. As can be seen in the formula for the strategy score, the rational agents base their decision on their neighbour's result score so that a purely rational player would ignore the neighbour's social influence. Whereas a less rational player would base their decision predominantly on the social rank their neighbour has. The *objectives* for each agent is to choose the "optimal" strategy to use in a prisoner's dilemma, played with a random player in the network. For the *adaptation* and *learning* the player can switch strategies based on previous evaluations. These strategies are imported from the Axelrod Library.

The interactions each agent has two possible interactions: playing the prisoner's dilemma and evaluating the strategy. The first interaction is done automatically an agent and random opponent play 10 games of prisoner's dilemma. Agents sense the previous opponents action, and get a resulting score for each game. These 10 score are averaged. The other possible interaction between agents is done during the evaluation for each strategy, where the rank, strategy and score of an agent in a connecting node is used to evaluate the performance of the strategy using equation 1.

Stochasticity plays a large role in the simulations. Each agent gets a rank and rationality drawn from a truncated normal distribution. The mean of these distributions are set by *input parameters* and the variance is set as equation 2 and the distribution is bounded by 0.001 and 1. Each agent is given a random strategy during initialization. And during the evaluation, the strategy with the highest score is chosen with a probability of $1 - switch\_random$ (which is also an input parameter). The player chooses a random strategy with a probability of *switch_random*.

The *observations* made per run are the following: occurrence per strategy in the population and the number of cooperations and defects played that iteration. Expected is that the *collective* will behave differently from the basic prisoner's dilemma where death and reproduction occurs. We expect this because a strategy has to outperform all other strategies under all conditions, meaning it should outperform each strategy one versus one and outperform the strategies when playing themselves. Expected is that an equilibrium is reached where a strategy is the largest group in the population but does not take over the whole population.

3.5 Initialization

During initialization agents the i-th agent is placed on the i-th node of the grid. The strategy of the agent is randomly chosen by using a uniform distribution between the options. The rank and rationality are both drawn from a truncated normal distribution between 0.001 (since we divide by the rank) and 1. The mean is a given input and the variance is dependent on the mean in the following way:

$$max\{\frac{1-\mu}{2}, \frac{\mu}{2}\} \tag{2}$$

3.6 Input data

The model takes as input data a strategy set and a network. The strategies we use are certain strategies from the Axelrod's first tournament, namely:

- Cooperator - always cooperates
- Defector - always defects
- Tit For Tat - starts with cooperating, and afterwards copies the previous move of his opponent
- Random - randomly plays cooperation or defect with equal probability
- Win Stay Lose shift - starts with cooperating, but shifts to another strategy when the other player defects

The network will contain one agent per node and remains static during the whole model run. The edges in the network will be used to determine each agent's social circle during the strategy evaluation phase of an iteration.

3.7 Sensitivity Analysis

Sensitivity analysis was performed on both the local and global level. At the local level, one-factor-at-a-time (OFAT) sensitivity analysis was performed. At the global level, the Sobol [21] method was implemented.

The analyses were conducted in a similar fashion. Both had three input parameters, namely the *rationality*, *rank* and *switch random* parameters as described earlier. The rank and rationality were bounded over their full range: $[0, 1]$. Because a probability of 1 for randomly switching strategy would make the model outcomes impossible to interpret, the *switch random* parameter was bounded $[0, 0.5]$. From these ranges, 10 distinct samples were taken. Each model was set to 50 steps (so agents played 500 games per run in total), and would then ran 50 times, over which the average was taken.

As discusses before, we observed two output measures. In one group the number of occurrences of each strategy was tracked. In the second group the total amount of times agents chose to either cooperate or defect. These amounts could then be translated to create a distribution within each of the two groups.

4 RESULTS

4.1 Base Case

First, the state and operation of the model after the combination of the ABM and Facebook network will be discussed. Figure 2 shows the case when all players are fully rational, only maximizing utilities which is referred to as the base case in this paper. After simulating the IPD model a hundred times, we obtain the performance of these five strategies in the evolutionary IPD game. The system stabilized after the tenth iteration, and defects present the highest percentage among these strategies. IPD does not have a strategy in the network which dominated the game under long-term evolution, and neither cooperation nor defection can spread over the network. On the contrary, although the proportion of people adopting the defect strategy is the largest, the defect strategy is only stable at about thirty percent in a hundred simulations.

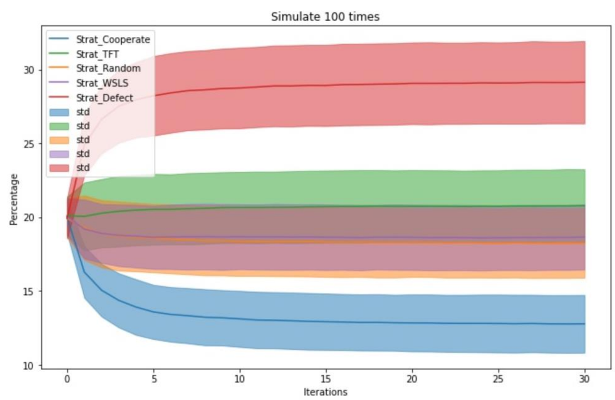

Figure 2: Percentage of strategies through IPD games with $rationality = 1$, $rank = 0$, $switch\_random = 0$. Simulate 100 times.

The reason is that the system has reached a dynamic equilibrium in about ten iterations, and strategies spread in the network will reach a relatively stable structure. At the beginning of the evolution game, the always defect strategy can significantly maximise the payoff. When more than thirty percent of the players keep this strategy in the network, more and more people use defect strategy merely obtain lower utility. Then players will adopt cooperate-based strategies to achieve higher payoff. This dynamic equilibrium finally obtain the result of Fig 2 under a hundred simulations.

Not only the percentage tends to be stable, but the standard deviation also tends to be stable and not decrease as the number of iterations increases. Standard deviations are not decreasing as the rise in the number of iterations. The reason may be that different strategies are randomly assigned to different positions in the network before the game started. Therefore, we believe that these strategies will be distributed in the network in a unique and stable structure after evolutions and maintain the dynamic equilibrium.

Unlike the base case's complete rationality, when the player is not entirely rational and is influenced by other players, the percentage of different strategies will gradually stabilize as the number of iterations increases, and there are continuous fluctuations due to the stochastic *rationality* and *rank* as in figure 3. Similar to the base case, the ABM in the network gradually forms a stable structure, and slight fluctuations exist because of the randomness.

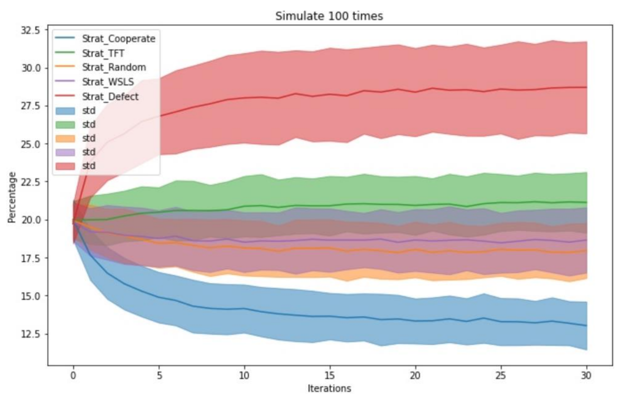

Figure 3: Percentage of strategies through IPD games with $rationality = 0.2$**,** $rank = 0.5$**,** $switch\_random = 0.3$**. Simulate 100 times.**

4.2 OFAT

In order to perform a well-structured analysis, the results of both output measures (amount of defects/cooperations and the occurrence of the strategies) of the local sensitivity analysis were grouped. This was done by first fitting the data points using the Least Squares method and categorising the resulting equation in the following manner: increasing if the slope is bigger than 1, decreasing if the slope is lower than -1 and otherwise we consider this output measure unaffected.

Note that the scales on the graphs are not identical, which could cause misinterpretations.

4.2.1 Influence of the rationality parameter. Figure 6 shows the results for the occurrences of cooperations and defects when the *rationality* parameter was varied. We see that the division in strategies is fairly equal, with their occurrence being around the 50 % mark. However, there is a clear trend showing that agents will defect more often when they are more rational. While the difference is not substantial over the whole range (the relative mean change is about 4%), we still consider this a noteworthy result as the upward/downward slope is obvious.

We did not expect this result, because the Axelrod first tournament showed that nice strategies performed better. Thus, we expected rational agents (which focus solely on the game output) to play cooperation more often and even take over the whole network. However, in a fully rational cooperating network, a single defector would always outperform all the other agents, since the payoff is higher for playing (D,C) than for playing (C,C). This would in turn influence other agents to defect because they are fully rational and would thus adopt the defecting strategy. As such, it is inevitable for an equilibrium between cooperators and defectors to emerge. The payoff matrix determines this equilibrium; for instance, even higher payoffs for defecting would result in even more agents playing defect.

Note that the variation remains equal amongst the whole parameter range - the *rationality* parameter thus has no effect on the amount of variation.

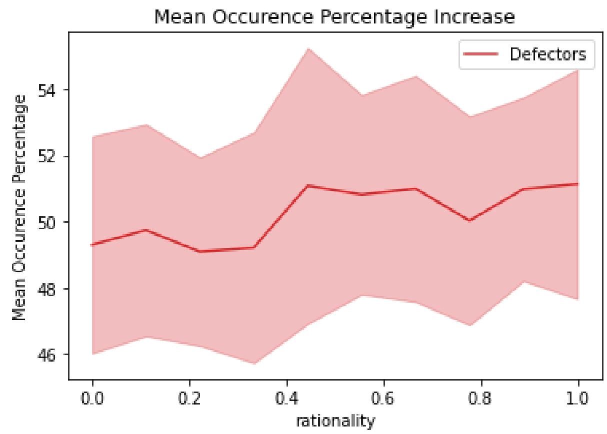

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Figure 4: Mean percentage of the amount of defects that were played each iteration.

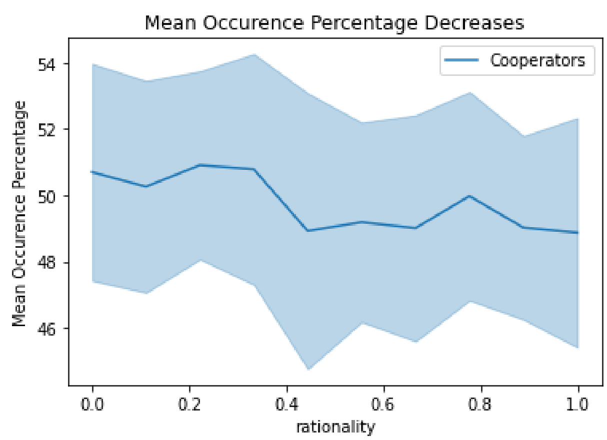

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Figure 5: Mean percentage of cooperations that were played each iteration.

Figure 6: Results of OFAT sensitivy analysis for the *rationality* parameter (with 68% CI).

The output measure results regarding the strategies occurrences can be seen in Figure 9. These graphs also show that the defecting strategy prevails by a significant margin and that its occurrence increases when the agents become more rational. The second-best strategy is TFT, which makes sense as it performs well against all the defectors and the other strategies. The cooperating strategy performs by far the worst out of all of them, which also seems logical as it receives a payoff of 0 against all the defectors.

Again, we see no difference in the variance when the *rationality* parameter is varied. However, we do see that the variance increases when the mean occurrence of a strategy increases.

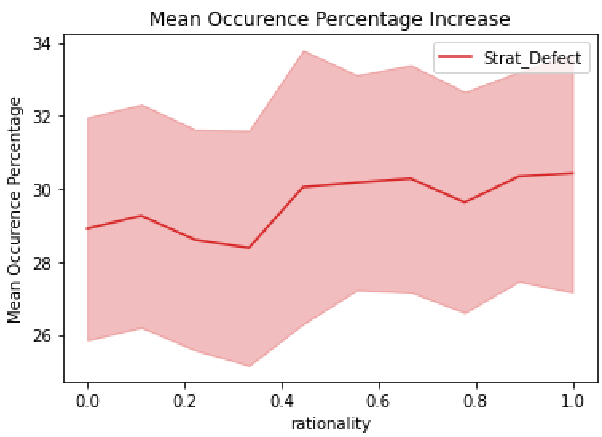

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Figure 7: Mean occurence of the defecting strategy (the only increasing strategy).

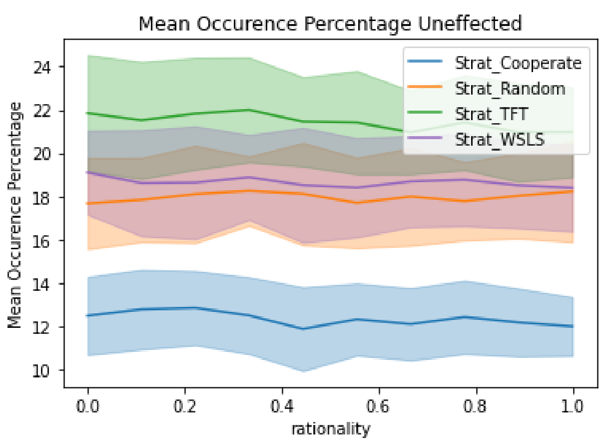

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Figure 8: Mean occurence of the other strategies.

Figure 9: Results of OFAT sensitivy analysis for the *rationality* parameter (with 68% CI).

4.2.2 Influence of the rank parameter. Figure 12 shows the results for the occurrence of cooperations and defects when the *rank* parameter was varied. We see a sharp increase in the number of defectors when the rank input parameter gets higher and a sharp decline in cooperators. We consider this the effect of the way our social influence is calculated in equation 1. The non-rational term of the equation looks at the relative difference in ranks between two agents. As a result, the non-rational term will contribute more to the total social influence when the rank is lower (because the relative difference between 0.1 and 0.01 is ± 9 times higher than the relative difference between 0.99 and 0.9, even though their absolute difference is the same). Thus, the higher the *rank* parameter gets, the more weight is given to the rationality term and this again results in an increase in defectors to reach the natural equilibrium.

Note that we can see an edge effect in both graphs. For the defectors, we see a small drop near the end of the parameter range and for cooperators we see a small increase near the same end. This can be explained by the truncation of the rank parameter. When this input parameter is set to 1, a lot of agents will have the exact same social hierarchy position, i.e. their influence will have the least effect.

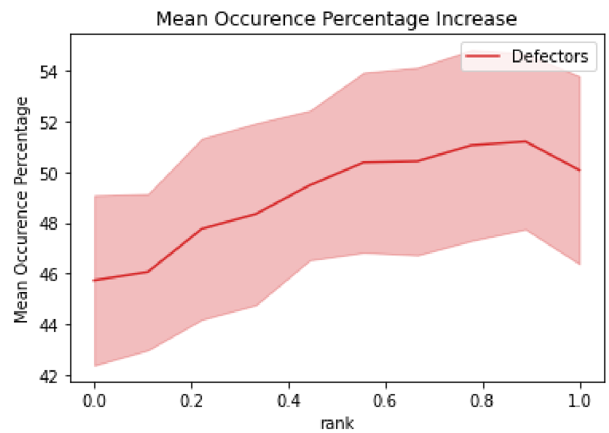

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Figure 10: Mean percentage of the amount of defects that were played each iteration.

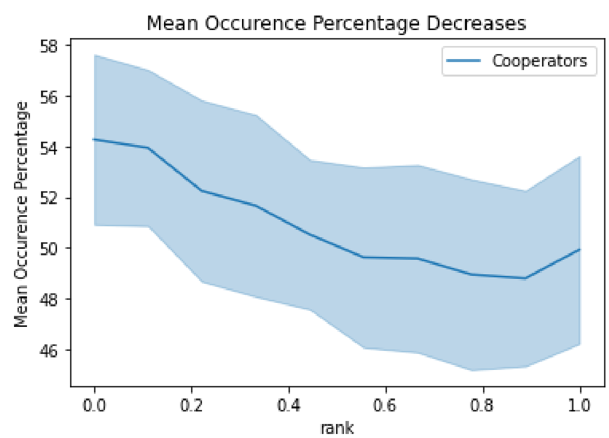

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Figure 11: Mean percentage of cooperations that were played each iteration.

Figure 12: Results of OFAT sensitivy analysis for the *rank* parameter (with 68% CI).

The output measure results regarding the strategies occurrences can be seen in Figure 15. As expected, we again see that defecting is the prevailing strategy and that it increases with more than 10% when the mean rank goes up. This is a significant gain at the expense of the cooperating and WSLS strategies. This makes sense as these strategies are vulnerable to the defecting strategy. While this is evident for the cooperating strategy, this is also the case for WSLS as the WSLS strategy switches to cooperating when it defects against another defector. This seems counter-intuitive, but works really well to escape defect-loops - except when you are playing against a defector.

We omitted the graphs for the unaffected strategies TFT (average mean of 21.3) and Random (average mean of 18.1) to prevent an unnecessarily extensive analysis. However, the graph can be found in appendix 6.1. TFT is robust against all kinds of strategies, and random can also not be taken advantage of, so it makes sense that their prevalence is unaffected.

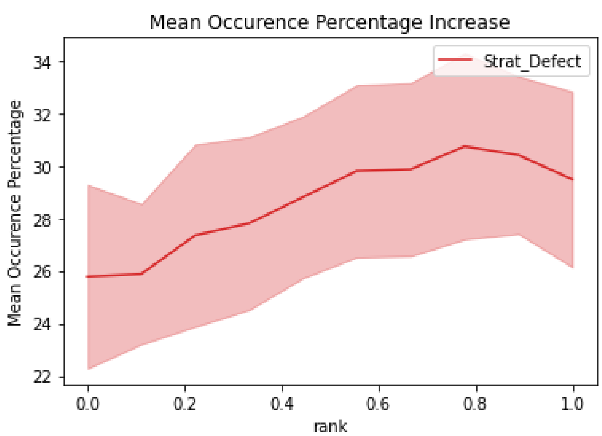

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Figure 13: Mean occurence of increasing strategies.

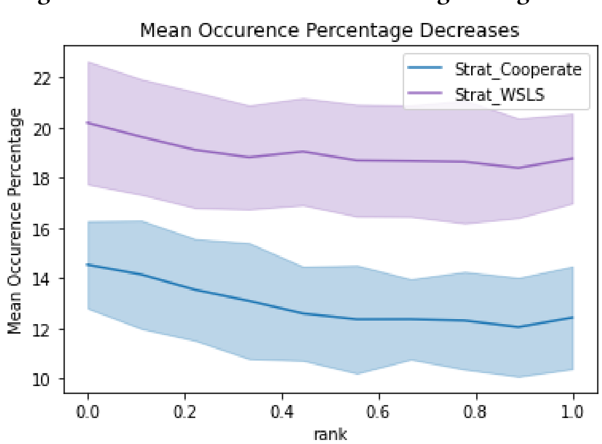

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Figure 14: Mean occurence of decreasing strategies.

Figure 15: Results of OFAT sensitivy analysis for the *rank* parameter (with 68% CI).

4.2.3 Influence of the switch-random parameter. Figure 18 shows the results for the occurrence of cooperations and defects when the effect of the *switch-random* parameter was investigated. We see a marginal effect of this parameter with the opposite effect as for the other parameters: there is a weak upward trend for the number of cooperators when the *switch-random* parameter increases. This is more notable at the end of the range, where the slope gets steeper. This result is expected as there are more nice strategies than mean strategies, because 3 out of the 5 strategies will not defect on its own. So, when there is a high chance of picking a random strategy at each step, the chance is higher that a nice strategy will be picked. This results in a constant influx of new cooperators, even if they perform worse than defectors. We also deem it possible that due to the constant high presence of nice strategies, they perform better than the mean strategies.

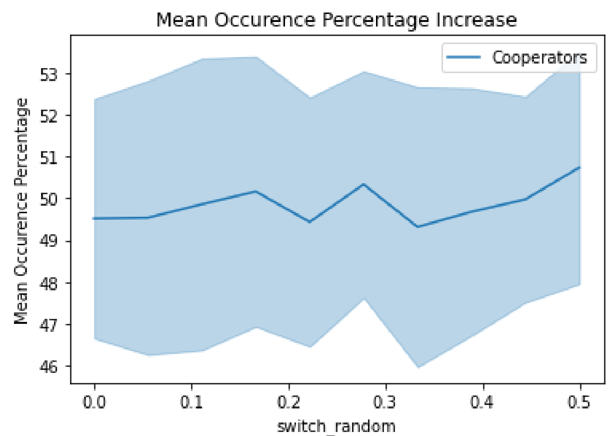

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Figure 16: Mean percentage of the amount of defects that were played each iteration,

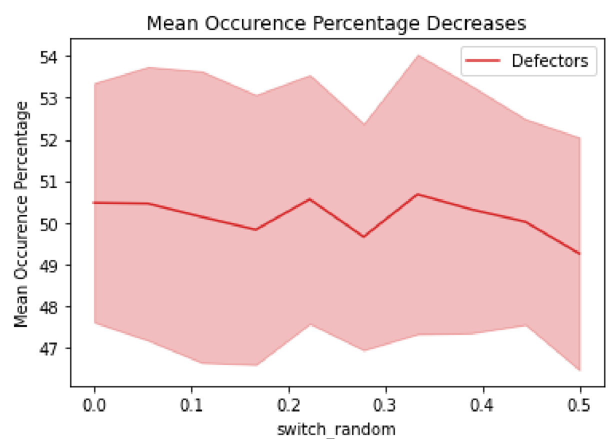

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Figure 17: Mean percentage of cooperations that were played each iteration.

Figure 18: Results of OFAT sensitivy analysis for the *switch-random* parameter (with 68% CI).

The output measure results regarding the strategies occurrences can be seen in Figure 21. Again, we see a very small difference, but with a clear trend. The cooperating strategy gains more traction at the expense of the random and WSLS strategy, when the *switch-random* parameter is increased. We also see a 50 % reduction in variance in the cooperating strategy near the end of the range. While this makes the case for nice strategies performing better with a high value for the *switch-random* parameter, we also see a reduction in the WSLS strategy - which is also a nice strategy. This is an unexpected result, as we would expect the defecting strategy to be the one to concede a little.

The graphs for the strategies whose presence were unaffected by the *switch-random* parameter were again ommitted for clarity and can be found in 6.2. The mean for the defecting is 30 and the mean for TST is 21. This means that the defecting strategy is still the prevailing strategy and that the cooperating strategy is still losing out across the whole range.

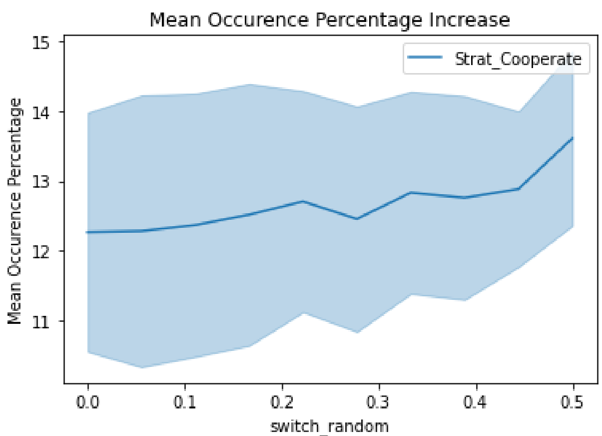

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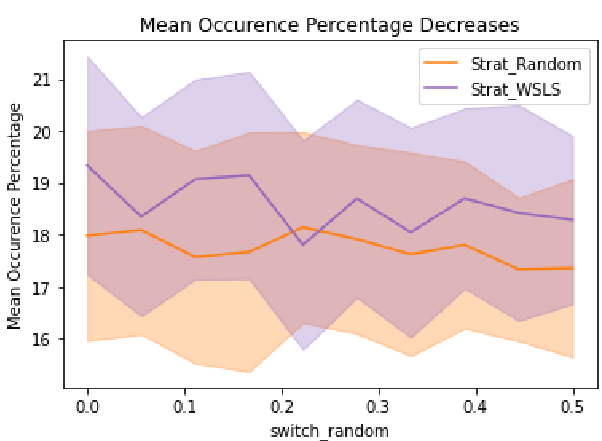
Figure 19: Mean occurrence of increasing strategies.



.5

Figure 20: Mean occurrence of decreasing strategies.

Figure 21: Results of OFAT sensitivy analysis for the *switch-random* parameter (with 68% CI).

4.3 Sobol

All results of the global sensitivity analysis were plotted per order, per input parameter. For this research, only the first- and total-order sensitivities were taken into account. Considering the amount of plots and their similarities, here only the most interesting results are discussed. All other results can be found in 6.3. To give more insight in the results, the error bars of the sensitivities of each output parameters in the plots were coloured. In each plot, the output parameters that were least sensitive to the variance of the corresponding input parameter, got a green error bar. For the most sensitive output parameters the error bar was red. For those that were relatively average, the error bar was turned orange. It is important to note that green error bars in one plot could relate to much more sensitive output parameters than those that have a red error bar in another plot. This is because the colours were assigned based on relative sensitivity within the plot, not overall.

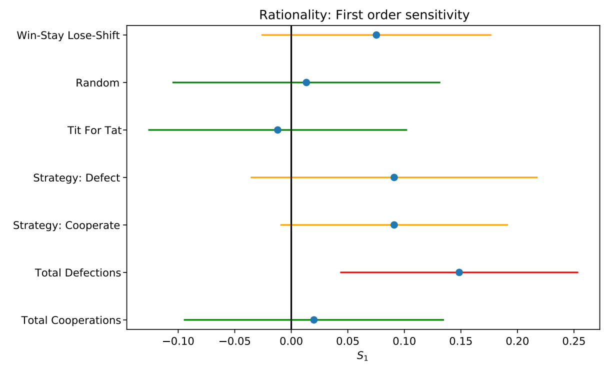


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Figure 22

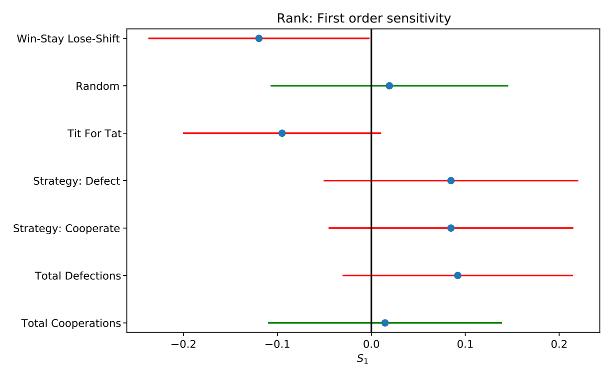

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Figure 23

Figure 24: First-order Sobol sensitivity analysis. 9(a): Rationality. 9(b): Rank.

Figure 24 shows the first-order sensitivities for the rationality and rank input parameters. First thing to notice is that the random output parameter was very insensitive to both input parameters shown, as well as to the switch random input parameter. Furthermore it is interesting to note that variance in the rationality and rank input parameters merely influenced variance in the total amount of cooperations, however heavily (relatively speaking) influenced the variance on the total amount of defections. A final observation is that the Tit For Tat strategy is much more sensitive to variance in the rank than variance in the rationality of agents.

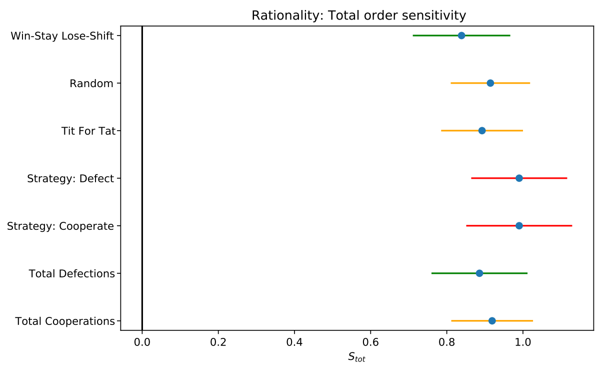

Figure 25: Total-order Sobol sensitivity analysis: Rationality.

Figure 25 shows the total-order sensitivity for each strategy corresponding to the rationality. The colours of the error bars show that the strategies of always defecting and cooperating are most sensitive and Win-Stay Lose-Shift is least sensitive. However, what is more crucial, is that all strategies, as well as the total amount of cooperations and defections, were very sensitive towards the rationality. Even more so, for the rank and switch random input parameters, similar results were found.

	Rationality	Rank	Switch Random	Sum
Win-Stay Lose-Shift	0.075	-0.12	0.013	0.208
Random	0.013	0.019	0.009	0.041
Tit For Tat	-0.012	-0.095	-0.062	-0.169
Strategy: Defect	0.091	0.085	0.034	0.209
Strategy: Cooperate	0.091	0.085	0.034	0.209
Total Defections	0.149	0.092	0.095	0.336
Total Cooperations	0.02	0.015	0.058	0.092

Table 2: First-order Sobol sensitivity indices

Table 2 shows all first-order indices, as well as the sum over the absolute values of the input parameters for each output parameter. As can be seen, this sum is highest for the total amount of defections, being quite low at 0.336. This indicates that the individual input parameters have relatively low influence on the variance of the output parameters, and most can be accounted for by interactions between the input parameters. Finally, an interesting find was that some of the first-order indices were negative, which suggests that not enough distinct values were created when sampling the input data.

5 CONCLUSION & DISCUSSION

As has been said above, despite our initial expectation based on the original Axelrod tournament, it has been shown that when strategy's performance is calculated based on a match with a single opponent, the defecting strategy wins even in a highly rational society. This was found to be due to the difference in our model from the original tournament. In the original Axelrod tournament, each round consisted of players playing a match against all other opponents. Given that the (C,C) combination has the second greatest payoff for both players, the fact that the initial cooperators will first suffer against defectors becomes irrelevant as the prize when playing with nice strategies makes up for the loss against the mean ones. However, when each is playing against a single opponent, a lower gain with a chance of the highest becomes more beneficial than the second best with a risk of the lowest prize. We find this result quite interesting as it highlights the difference between the long-term and short-term effect. It shows that the winning strategy (defect) suggested by the Game theory on average holds even in a match with responsive opponents as long as we are not looking at an overall achievement but an immediate gain.

Another interesting finding is that no strategy completely takes over. We have found that the 50 iterations of the game are more than enough for the population to reach the equilibrium state in the sense of the proportions of players with a particular strategy. However, the maximum mean percentage is around 30%, meaning that most of the players use other strategies. This could be due to the network topology and the fact that the agents only know their neighbouring strategies. However, given that the graph is connected (there is a path between every two nodes), in a fully rational population with a strategy that does do better then all others, a single prevailing strategy should exist. This implies a possibility that in the strategy set used for this research, there is no single best strategy. Further research can investigate a different set of strategies, possibly one where there is a single known winning strategy.

An interesting result of the OFAT sensitivity analysis is that the more rational the population is, the more will the players be defecting against each other. This is again confirming that it is more useful for an agent to defect in the case of a single match This is shown in the results of varying either rationality or rank parameter and is further confirmed by the opposite effect of varying the *switch random* parameter. With a higher probability of an agent choosing a random instead of the *best* strategy, the agents are more prone to cooperate. This confirms that the higher occurrence of defects is not due to chance, but better performance.

An interesting effect of social influence can be observed when the rank parameter reaches the value 1. The agents are made to be more likely to fall victim to the influence if they are ranked low themselves then if they are *already doing good* on the social ladder. However, this does not make a highly ranked individual fully rational. The social influence is having a reversed effect on this agent. A low ranked individual may consider a low performance strategy of a highly ranked individual as supreme, however, a highly ranked player may disregard the winning strategy because someone plays it with a low ranking. This difference is evident in the decline of Defectors when most of the agents are of the highest rank versus a rise when most of them are fully rational. This way of representing social influence could be further investigated. A formula looking at an absolute difference instead of a ratio in the ranking of agents could be showing a different form of influence. As mentioned in the introduction, *wisdom of a crowd* has multiple dimensions and those could be incorporated in the model.

During the global sensitivity analysis, the percentage of Random strategy showed to be unaffected by all of the parameters. This could be a sign of this strategy's performance is unaffected by the distribution of other strategies. However, it could be because of the network used for this research. Given that the Random strategy will do relatively well against all but Defector strategy, it could be that the network is formed in such a way that a stable amount of agents will always see it as the best one. This should be further researched by varying the number of agents in the model or using different network topologies that are more easily analysed.

As mentioned, it was found that all of the parameters bring value to the model, as the variance of varying a single parameter remains high despite the values on which the other parameters are fixed. This is in line with the intuitive idea that different combinations of rationality and influence level in society will bring different results. An important thing to note is that negative values have occurred during the Sobol sensitivity analysis, indicating that the parameter space was not sampled to a high enough extent. Ideally, the research would be repeated eliminating this problem, but this was not possible at this time due to time restraints. Another point for further research could be to see how changing the payoff matrix would influence the dynamics of the Prisoner's dilemma. It is interesting to see how different ratios between possible utilities would change the equilibrium state within the model.

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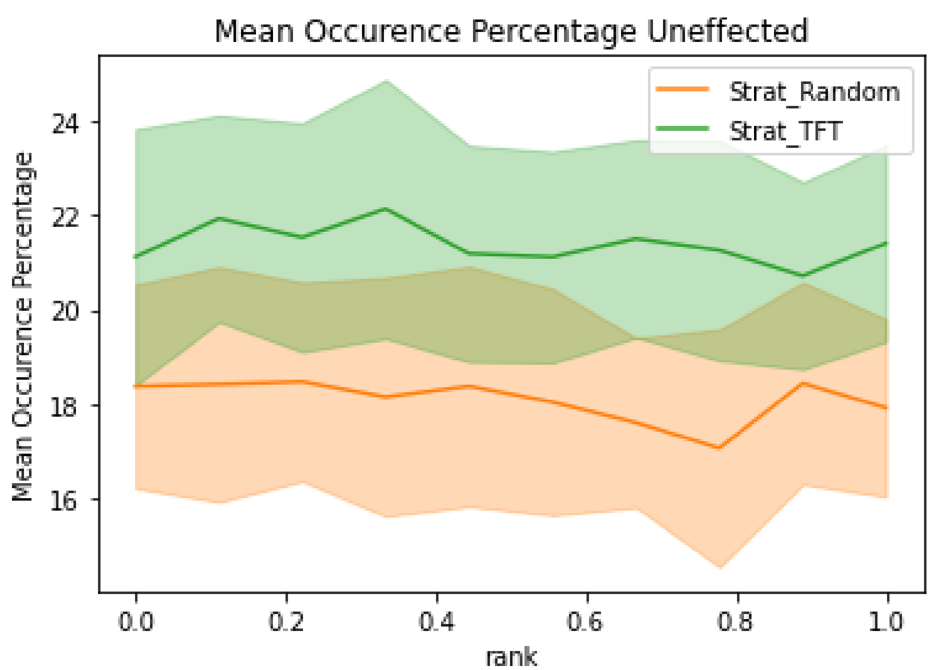
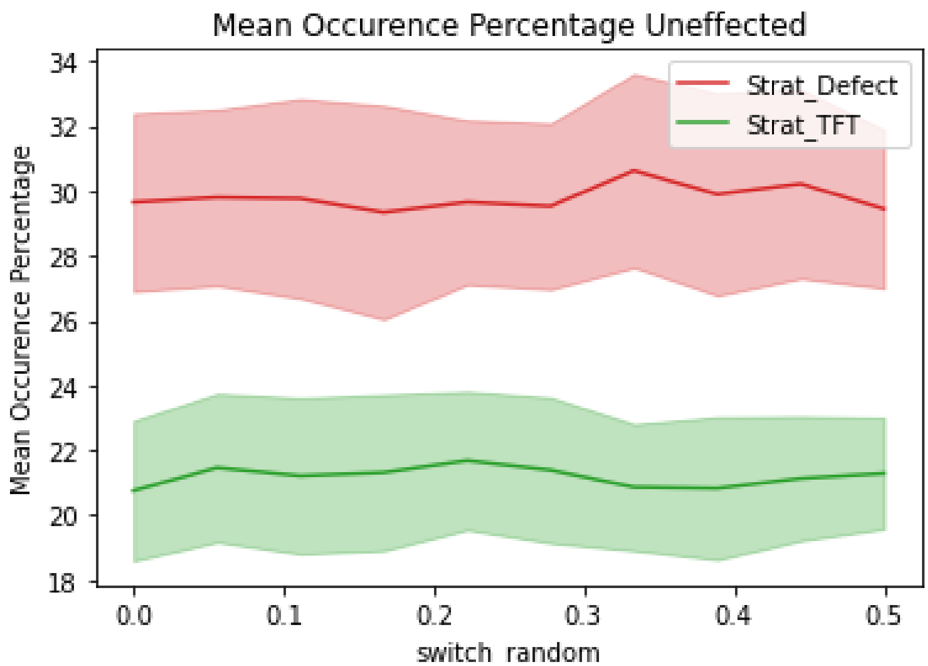
6 APPENDICES

6.1 Unaffected strategies found in OFAT analysis of rank parameter



6.2 Unaffected strategies found in OFAT analysis of switch-random parameter



6.3 Sobol sensitivity analysis

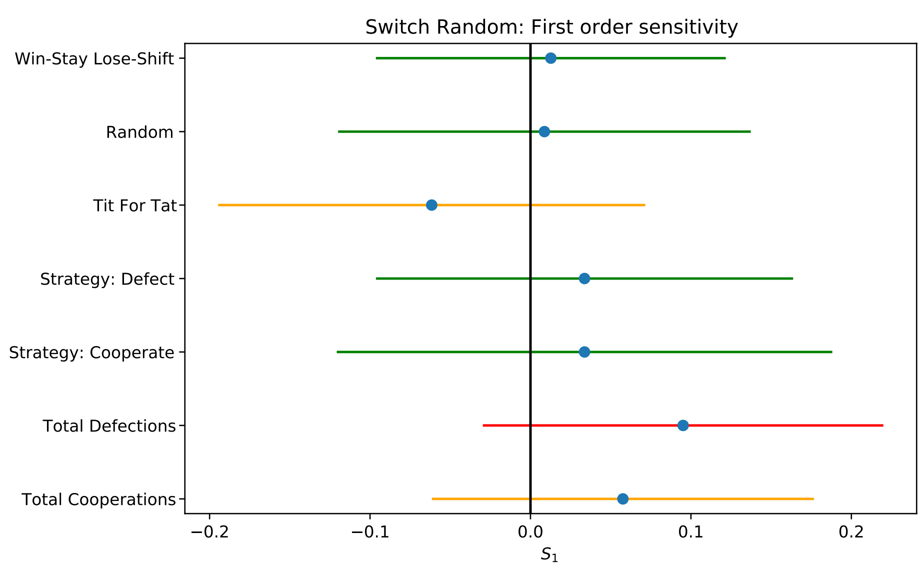


Figure 26: First-order sensitivity analysis: switch random

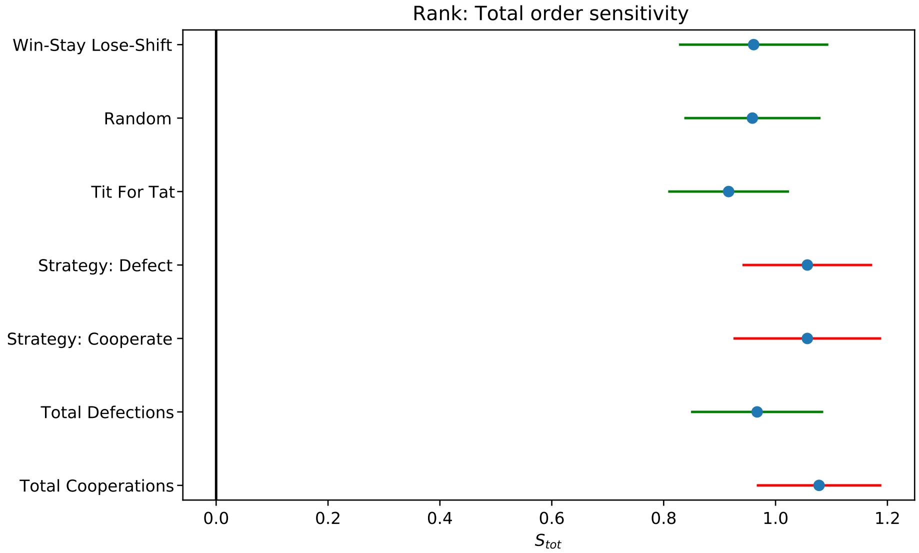


Figure 27: Total-order sensitivity analysis: rank

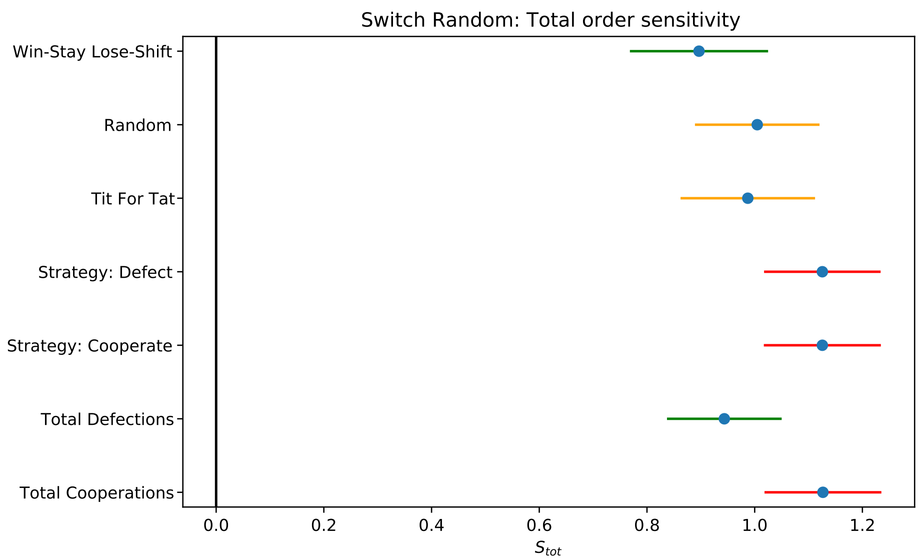


Figure 28: Total-order sensitivity analysis: switch random