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# A Networked Evolutionary Trust Game for the Sharing Economy

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A Networked Evolutionary Trust Game for the Sharing Economy

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Utrecht University

*Bachelor Thesis*

*Economics and Business Economics*

## Abstract

In the sharing economy, trust is of higher importance than in regular B2C interactions because there is no transfer of ownership and transactions sometimes take place in private space. Chica et al. (2017) developed an evolutionary trust game to unveil occurring dynamics and explain how trust could evolve in the sharing economy. This thesis adds the variable of network structure for the network of possible interactions to their model. Using agent-based modelling, the model is ran on networks with varying levels of community structure, systematically varying average degree, the community connectedness and game payoffs. We find negative correlations for degree and it is suggested that having more isolated communities has a positive effect on trust, but this is highly dependent on the reward for cooperating. Chica et al. (2017) showed strong interdependence between players of different strategies and found a strong influence of payoffs on the dynamics. The current research shows that a strong interaction with network structure should also be considered. The presented findings progress the field of evolutionary game theory, by learning from a specific application. Furthermore, findings also suggest that sharing economy platforms could enhance trust by emphasising or creating communities, depending on the risk and how clear benefits are to users.


*Keywords*: sharing economy, trust, evolutionary game theory, agent-based modelling, simulation, network structure, community structure¶

# A Networked Evolutionary Trust Game for the Sharing Economy

For a long time, ownership was one of the fundamental constructs of economics. Although shared consumption is as old as humankind (Belk, 2014), the internet has removed barriers for bringing providers and consumers together in the so-called sharing economy. It is estimated that by 2025, the global market size will reach $335 billion (Lieberman, 2015). Despite this, the concept of the sharing economy is not a homogeneous concept. It has been argued that the term is a misnomer (Eckhardt & Bardhi, 2015) and different kinds of C2C transactions with a social element have been labelled as sharing economy, causing inconsistency in the literature (Habibi, Kim, & Laroche, 2016). In this paper, the following definition by ter Hurne, Ronteltap, Corten, & Buskens (2017), will be used: "[The sharing economy is] an economic model based on sharing under-utilised assets between peers without the transfer of ownership, ranging from spaces, to skills, to stuff, for monetary or non-monetary benefits via an online mediated platform."

The fact that transactions occur between peers, and that there is no transfer of ownership make it require a considerable amount of trust (McNight & Chervany, 2001; Botsman 2012), and the ability to create and maintain trust is often identified as one of the critical factors for a sharing platform's success (Ufford, 2015; Strader & Ramaswami, 2002). To examine the role, moderators and antecedents of trust in the sharing economy, various methods have been used in the past. Mainly survey data, but also case studies, econometric analysis, field interviews and experiments are employed (Gefen, Benbasat, & Pavlou, 2014), each with their own limitations.

Chica, Chiong, Adam, Damas & Teubner (2017) were the first to introduce the usage of evolutionary game theory (EGT) in an agent-based model (ABM) to explore system dynamics and population end states for the spread of trust in the sharing economy. They simulated virtual agents having sharing economy interactions and showed that trust can be formed when benefits are high enough, except if the ratio of trusting and trustworthy players is low from the start. Even when the reward values are low, a situation of trust can still emerge as long as the starting population included enough trusting and trustworthy players. This methodology of combining

EGT with ABM is relatively new to the field of economics, and gives new possibilities: ABM can generate amounts of data, with exact control over 'treatments' simply impossible with experiments, and the fact that a simulation has to be programmed requires the research to be very precise about assumptions. However, Chica et al. (2017) limited the agents in the reach of their interactions by putting them on an empirically observed email network. It is unknown to what extent the specificities of that network could have influenced results. This thesis will build upon their model and methods by adding network structure as a model variable, and creating software which allows for visual inspection of the network over the course of the simulation. The simulation will be run multiple times, on different network structures, while keeping the number of nodes constant, extending this application of EGT on the sharing economy.

This paper's scientific contribution will thereby be twofold. Firstly, it contributes to the development of a theoretical framework using EGT and ABM combined with aspects from network science. Although the perspective from network science has previously been used in the context of the sharing economy to explain the spread of information (e.g. Buskens, 1998; Frey, Buskens, & Corten, 2019), research on how the network structure affects emergence of trust in isolation of reputation and communication is relatively new. In this line of theoretical research, all the other methods of enhancing trust are omitted, and the only 'motivation' for fictional players are the payoffs a trusting or trustworthy strategy can bring them. Developing this experimental application to the sharing economy could advance the method as a whole.

Secondly, because the game design is tailored to the sharing economy, this research might result in new insights for sharing economy platforms on how to enhance the aspect of trust that is influenced by network structure. Although there is little data available, it can be theorised  platforms have different networks of possible and occurring connections. Determinants of structure could include selection based on geography (e.g., in the case of tool or other small asset sharing), field of interest (e.g., book swapping), sharing a destination (e.g., ride or home sharing), or homogeneity effects within the network as shown by Schor, Fitzmaurice, Carfagna, Attwood-Charles, & Poteat (2016). Testing the effects of network structure on trust in isolation of other means could help explain why trust spreads differently on different platforms. Besides explanatory power, knowing about the extent to which the spread and stability of trust are influenced by network structure could possibly be used by platforms to enhance it.

To resemble a structure created by the selection and homogeneity described above, this research will use networks with a community structure, a common characteristic of networks (Girvan & Newman, 2002; Fortunato, 2010; Porter, Onnela, & Mucha 2009). A community structure was also observed in the email-network used by Chica et al. (2017) as foundation for their model (Guimera, Danon, Diaz-Guilera, Giralt, & Arenas, 2003). In this structure, nodes are primarily connected to peers in the same community, creating different highly clustered communities, while a smaller part of the edges is in between communities.[1] There are two reasons why this structure is particularly useful as a concept. Firstly, it is relatively simple to comprehend and apply to the real world. Homophily and other causes of clustering can be theorised or observed by an outsider without knowing the exact network structure; the concept of linkage between them is also relatively easy to grasp. The second reason is scalability. Because the number of edges changed from intra-community to inter-community is a relative concept, unravelled dynamics could possible apply to different scales. This ratio of edges changed will be referred to as the variable ‘rewiring’ throughout this paper.

The research will proceed as follows. In section II, some theoretical background and related work will be presented, followed by the technical details of the model in section III. Section IV presents the setup of the experiments and their results. Finally, conclusions are presented in section V, followed by some limitations, implications, and possible directions for future research.

[1] In the network science literature, an individual is referred to as a ‘node’. In game theory context the individual is referred to as a ‘player’, while in the context of simulations it is often called an ‘agent’. These refer to the same thing. A connection between two nodes is an ‘edge’.

# Background and Motivation

## Trust in the Sharing Economy

As stated in the introduction, trust is a critical factor for the sharing economy. Participants need to be sure that transaction partners do not behave opportunistically and deviate from the agreement made. Because there is no transfer of ownership, providers risk damage or misuse of their assets. Consumers, on the other hand, usually do not have an established seller or governing institution to fall back to in case the asset is not as promised. This uncertainty makes the effects and likelihood of opportunism in C2C transactions more severe than in traditional B2C interactions. Additionally, when a transaction involves co-usage (e.g., ride sharing, renting out part of your house/couch), its quality is dependent on the experience with the provider, adding an extra level of complexity, and more need for a trust relationship between provider and consumer (Karlsson & Kemperman, 2017).

Common ways for platforms to create and maintain trust include binary or scalar ratings (Teubner et al. 2017; Zervas et al. 2015), subsequent reviews about the transaction (Abramova et al. 2015; Bridges and Vásquez 2016), host self-disclosure by means of personal descriptions and pictures (Ma et al. 2017; Tussyadiah 2016; Ert et al. 2016; Fagerstrøm et al. 2017; Teubner et al. 2014), or more formal measures like insurance and identity verification.

However, even in the absence of these measures, trust and cooperation can emerge. In the last two decades, the search for models accounting for complex cooperation behaviour in social, economic and biological systems has inspired a new body of interdisciplinary research that uses the methods of EGT (Smith & Price, 1973; Smith, 1998). EGT acknowledges the fact that the outcome of a system is more than the sum of pairwise interactions; it dismisses the assumption of rationality and introduces the concepts of a player population and player fitness. Fitness in this context means the sum of payoffs for an individual received during games. In EGT, successful behaviour spreads throughout the population by evolution, which is not (necessarily) rational decision making. The evolution rule often entails that players with unsuccessful strategies, and therefore a low fitness, die off, and get replaced by players with high fitness. The framework can also be used to simulate learning in an unchanging population, as is done in the presented sharing economy model.

An insight from EGT very much applicable to this model, is that when strategy distributions change, the relative fitness of the remaining strategies may also change. The fitness landscape is not static, but it also evolves as the distribution of strategies changes (Izquierdo, Izquierdo, & Sandholm, in press). On its own, this does imply that Pareto-optimal strategies, which benefit the whole population (in this model, being a trusting or trustworthy participant of the sharing economy), will necessarily survive. Cooperating with another player has a risk, and being opportunistic is often the best strategy in an isolated game, so a situation of trust can be highly unstable, and a single player with an opportunistic strategy can make the whole population move to a situation of distrust (Abbass, Greenwood, & Petraki, 2016). In order to explain how a situation of trust and cooperation can still emerge, the topology of the community is considered.

**Structure as a Solution**

As explained above, it has become clear that in zero-dimensional systems, where every player can interact with every other player, cooperation does seldom emerge without any other incentives. This is why the network structure of interactions should be considered. This idea already started with Nowak and May (1992), who were the first to depart from well-mixed populations, and put simulated agents playing prisoner-dilemma (PD) games in a two-dimensional space, where each agent could only interact with eight direct neighbours. A phenomenon that became visible is that the success of cooperative strategies often originated in the corners of the space, suggesting some protection from the network can be beneficial. Since the first exploration on a 2D grid, the emergence of network science as a discipline has provided tools for further research, and it has become clear that being embedded in a network structure of some sort can lead natural selection to select cooperative behaviour in game theoretic models (Rand, Arbesman, & Christakis, 2011).

Some more expectations can be inferred from closely related research. Simulations from Buskens & Snijders (2016), show that more centralisation[2] and less segmentation increases payoffs in 2x2 coordination games in a limited part of the reward space. Together with PD games, coordination games are the classic abstraction used when talking about cooperation in a network structure (e.g., Ellison, 1993; Anderlini & Ianni, 1996). A characteristic of the coordination game is that success is mostly dependent on the speed with which signals can propagate throughout the network. This is why models with Small-World characteristics[3] are successful: they display a shorter average path length and more synchronisability (Watts and Strogatz, 1998; Watts, 1999). Both centralisation and degree[4] can contribute to this, see Cassar (2007) for an overview of experimental evidence.

For social dilemmas, the speed with which signals or behaviour can travel through the network might not be the only determinant of success. Various theoretical approximations and simulations about the influence of network structure on PD games have been carried out. Abramson & Kuperman (2001) varied a structure from a regular ring lattice[5] to a completely random network and found a positive relationship between the amount of rewiring towards randomness and the number of defectors. Santos & Pacheco (2005) simulated snowdrift (SD) and PD games, in which they found the first game to be significantly more successful on a regular lattice than in a more random network. It is when expectations are inferred for the sharing economy trust model that the main issue for this kind of research is encountered: there is no mathematical framework to compare games, nor enough ways to quantify network structure to approach these problems as an exact science. Dynamics that occur in PD or SD games cannot be directly translated to the trust game that is used as an abstraction for the sharing economy.

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[2] The existence of nodes that are situated on a lot of all possible shortest paths between nodes

[3] Small World networks are a specific type of network structure with a high clustering, but a low average path length, as first recognised and described by Watts & Strogatz (1998)

[4] The number of edges a node has

[5] A regular network with the highest possible clustering for each node, but also an high average path length (Watts & Strogatz, 1998)

More complex game simulations that include the concept of individually placed trust instead of simultaneous cooperation like PD and SD games were carried out by Chica, Chiong, Kirley, & Ishibuchi (2018). They use an N-player trust game, closely resembling a public good game. Their first finding, in line with Abbass et al. (2016), is that strategies of trust never survive in an unstructured population. Since an untrustworthy player can interact with anybody, their distrust will spread quickly. Conversely, sparsely connected structures are better for the promotion of trust via social diversity in smaller clusters, in line with ideas from Santos, Santos, & Pacheco (2008). Both these sources use games with different strategy setups, that seem more dependent on the local neighbourhood than the simpler 2-player trust games used for the sharing economy, still, the idea that sparsely connected clusters increase performance is insightful for our application.

**Community Structure**

This research will use community structure as a starting point for variations in the network. This idea is found in research from various disciplines, but not often in the context of social dilemmas and trust. Fang, Lee, & Schilling (2010) introduced the concept of community structure, and the rewiring between communities as community connectedness, to explain why some companies are good at fostering innovation. They present the subgroups as shelters for ideas, enabling them to survive and show their success, rather than being extinguished through fierce competition in the population as a whole. In biology, there are similar reasons to believe a community structure can benefit cooperation. Theoretical and computational works by Nowak and May (1992; 1993) and Nowak, Bonhoeffer, & May (1994) predict and show behaviour where cooperators and defectors coexist in clusters in the same network.

Prior to Chica et al. (2017), little research went into the specific dynamics producing these end states, which they showed to be dependent on the payoffs and starting distributions. It is difficult to draw expectations from other research because little research combines varying degree, structure and payoffs within the same simulation, while it could be suspected that these influence each other. This paper might be the first to vary these three factors at the same time. Additionally, a graphical user interface (GUI) makes it possible to explore the dynamics in even more detail, by observing them in two-dimensional space, making more intuitive understanding of observed results possible.

## The Networked Sharing Economy Model

The influence of the network structure of possible connections will be explored using agent-based modelling (ABM), where agents are programmed to behave within the framework of Evolutionary Game Theory (EGT). The simulation will run in NetLogo, a modelling environment especially built for exploring behaviour in complex systems using an agent-based approach. The basic premise of the simulation is as follows: a constant population of agents with pure strategies are matched based on the existence of a direct link within a network to play a trust game. After a certain number of games, agents will revise their strategy, comparing their payoffs to those of agents around them.

The details of the model as below are described mostly theoretically. Further practical and technical details can be found in Appendix 1 and the simulation's source code (available upon request).

### Game Definitions and Payoffs

Since this paper builds upon the first application of EGT for the Sharing Economy by Chica et al. (2017), the game definitions of the trust game will be the same. This social dilemma is characterised by a payoff structure in which the cooperative, Pareto-optimal, combination is unstable because each individual could gain a higher or less risky payoff when they choose a selfish alternative. The Provider is the trustor, while the consumer is the trustee. The strategies and their real-world explanation for each player are as follows:

- TP: a trusting provider who delivers an asset as agreed upon.
- UP: an untrusting provider who does not deliver, causing a small negative payoff for the consumer and a small positive payoff for themselves.
- TC: a trustworthy consumer who uses the asset decently.

- UC: an untrustworthy consumer, who misuses the asset, e.g., by damaging or stealing it, causing damage to the owner and a high payoff for themselves.

Table 1

*Payoffs in the Sharing Economy Trust Game*

| Providers | Consumers | |
|---|---|---|
| | TC | UC |
| TP | R, R* | -20, 40 |
| UP | 10, -10 | 10, -10 |

*Note.* When players interact with an agent with the same role (i.e., provider or consumer), no transaction takes place, and the added payoff is 0.

*By definition, the minimum and maximum rewards are 21 and 39 respectively, because of the game's definition by Chica et al. (2017)

Different payoffs likely change the evolutionary dynamics via the 'difficulty' or temptation to defect in the game (Chica et al., 2017; Chica et al. 2018), so the reward for cooperation will be one of the variables in the model. The reward value R will be varied covering this games' easy (39, 36), moderate (33, 30, 27) and hard (24, 21) spectrum, as identified by Chica et al. (2017).

It should be noted, however, that the non-sequential play and lack of communication make the game designed by Chica et. al. (2017) different from most trust games in the literature, so comparison to other trust games should be done with care. Further justification can be found in their paper.

**Strategy Update**

Agents adjust their strategies simultaneously after 50 games via an algorithm that simulates evolution. For this, the proportional imitation rule (Helbing, 1992) will be used. This update heuristic is in line with the idea of bounded rationality and incomplete information for an agent since it considers limited memory, and knowledge only about the payoffs of direct network neighbours (Schlag, 1996). During the strategy update procedure, an agent will first randomly select a neighbour to compare their strategy and payoffs during the previous rounds. If the selected neighbour had a higher total payoff, the revising agent copies the selected agent's strategy with a certain probability. This probability is equal to the difference between their payoffs in the previous 50 games, divided by the maximum theoretically possible difference (in these scenarios this is the difference between 50 * R and 50 * -20). The arbitrary structure of 50 games before reconsidering the strategy will be used for comparability with the trust experiment using EGT by Chica et al. (2017).

## Generating the Networks

Although some data is available on network structures of occurred transactions on sharing economy platforms (e.g., Teubner 2018), it is of limited use, since this paper is about the network of possible connections, as opposed to the transactions that have occurred in the past. Besides that, the network data in the literature is often from Airbnb, which has a more traditional provider-consumer structure (Cox 2017; Wired 2017). This structure is, although not precluded, inconsistent with the definition of sharing economy used here. Because of this, this research will use theoretical approximations of real-world networks.

For this paper, a custom algorithm for generating networks with a community structure was programmed. First, it assigns every node a 'community' and randomly picks the required nodes within the same community to connect. It is important to note that this random assignment of community is entirely independent of all other randomnesses in the model, like which edges are rewired or which initial strategy is assigned to a node. After the edges within the community have been formed, each edge will be rewired to a random node with the required probability determined by the level of community connectedness. When connectedness equals one, the result is a completely random network. In all other cases, the algorithm will result in a network with community structure, as can be detected with the conventional Girvan & Newman (2002) algorithm.

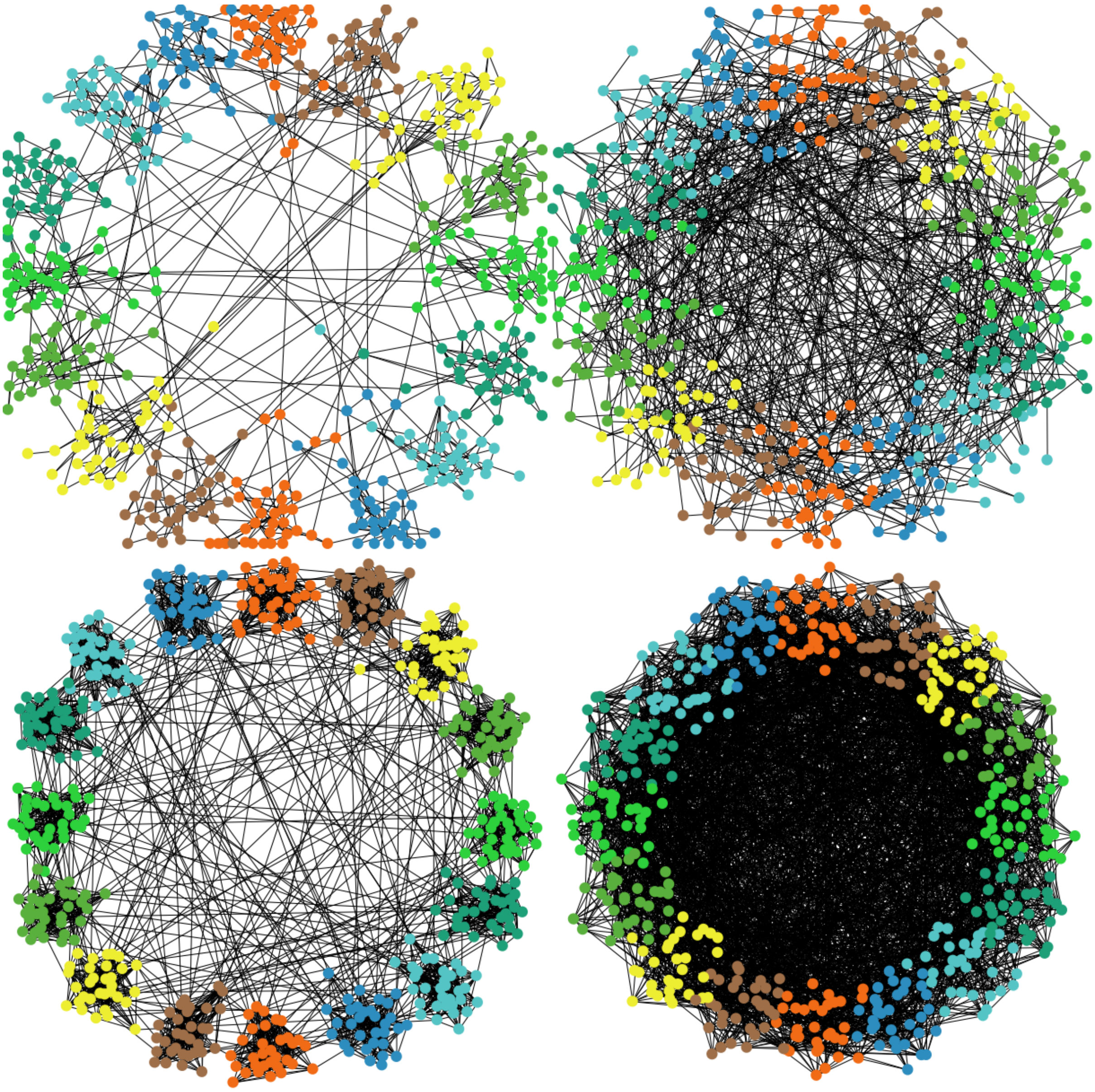

*Figure 1.* Example network layouts coloured by community with rewiring probability 0.04 (left) and 0.4 (right) and average degree 4 (top) and 14 (bottom).

## Experiments and Results

All results were obtained from simulations with a population of 512 agents, spread across 16 communities. Preliminary testing and analysis showed that this network size is large enough to ensure reasonable robustness and representative results at any combination of variables while being small enough to compute all simulations within the available timeframe.

This paper focusses on effects of average degree (D) and the amount of intra-community edges rewired to be inter-community after the initial communities have been set up (P). This value of P covers the concept of community connectedness. No available quantification of this concept of connectedness includes a scale, but in these experiments, a continuous range of network structures is created by varying the probability of rewiring edges between 0.01 and 1, creating a continuous range from communities connected to each other with a minimal amount of inter-community edges to a completely random network.

**Experimental Setup**

For each network, 'success' will be measured by summing all the payoffs gained during the simulation. A network that sustainably supports cooperation will gain high payoffs for a long time, while payoffs in a network with little trust present will quickly reach a state of low payoffs, or no transactions at all. From Chica et al., it is known that dynamics within this trust game can be vastly different for different payoff ratios. Because of this, the reward value (R) will be varied in interaction with the degree and rewiring, covering this games' easy (39, 36), moderate (33, 30, 27) and hard (24, 21) spectrum, as identified by them in their 2007 paper.

During preliminary testing, it was discovered that payoffs are most sensitive to rewiring when rewiring is low, so an exponential scale was chosen, testing relatively more values close to 0. Degree was started at 2 and tested up until 22 in steps of 2. Although this is not the limit of the variable space in which simulations end successful, an arbitrary limit had to be chosen. This leads to the following combination of variables: Reward (R) is varied [21, 24, 27, 30, 33, 36, 39], degree (D): [2, 4, 6, 8, 10, 12, 16, 18, 20, 22] and rewiring (P): [0.01, 0.02, 0.04, 0.05, 0.08, 0.1, 0.2, 0.4, 0.5, 0.8, 1] for a total of 770 possible combinations.

Because of randomness in the assignment of communities, rewiring of links and strategy evaluation, the simulation is non-deterministic. To approach the mean value for average total payoffs, every combination is repeated for at least 32 independent runs. With a very regular desktop PC, this took multiple days of non-stop simulations to compute, but with further code optimisation and access to a high performance computing cluster optimised for these kinds of calculations, the time could be a fraction of that.

## Analysis of the Results

First, some general remarks about the dynamics will be presented. Particularly on the 'balancing effect' that occurs in this game, presented by Chica et al. (2017). Thereafter, some specific areas in the tables of results will be highlighted, and further interpreted by looking at the details of some specific runs. This 'anecdotal' evidence is difficult to quantify but is in line with the exploratory nature of this research.

**Remarks on dynamics.** The balancing effect seems to be present to a certain extent at almost all variable combinations. This general pattern can be summarised as follows: at first, players with a UC strategy profit from their opportunistic behaviour, making their strategy spread. As a 'response' to this, UP players, a safe and risk-less strategy not affected by UC[6], become a substantial group within the population, driving out TP and TC, but most importantly UC. Agents with strategy UC cannot profit from agents with strategy UP. When a particular distribution (the flipping point is highly dependent on payoffs) is reached, TP and TC slowly regain ground. The playing field is now less risky with UC mostly or entirely gone. TP only forms a small risk to them, and they profit highly from the presence of each other. This balancing effect can be observed both at the community level or for the whole network at the same time when it is more connected.

Agents switching to an UP strategy could be interpreted as not partaking in the network's sharing economy at all; they are not risking to provide their asset and pick a certain but low payoff. At the micro level, we can see why this is a neutral context for TP and TC to spread. TP's influences are not affected by UP because they are both providers, and a TC can on average handle two to four times more UC's than TC's in order to still have a non-negative payoff. Another important fact

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[6] Throughout this research, players with a certain strategy will be referred to by the name of their strategy. Keep in mind, however, that it is not the strategy that evolves, but the players who 'decide' to use a strategy or not, based on its relative success.

is that TC and TP's payoffs are equal after a successful transaction, ensuring one does not become too much more successful in the network than the other, while in 'hostile' situations TP has slightly higher average payoffs than TC, spreading slightly more quickly, thereby creating a more favourable context for TC.

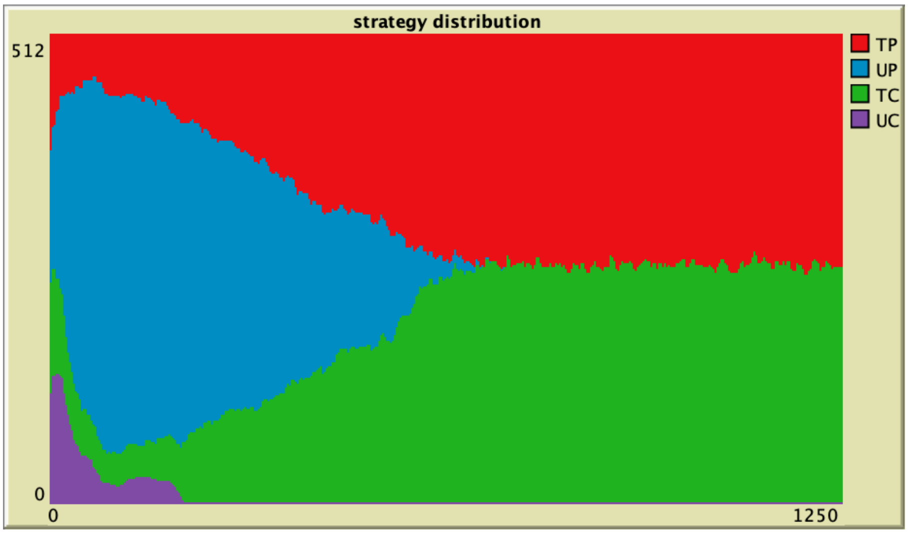


*Figure 2.* An example run that clearly contains the balancing dynamic as described by Chica et al. (2017) (D = 8, P = 0.01, R = 27).

However, looking at some of the runs in detail, it is observed that below 27 the success is dependent on complete absence of UC-players in the network. Because of the chosen strategy update rule, a strategy can never reoccur after having gone 'extinct'. This is good for the spread of trust, but problematic for drawing implications, since it could make the simulation end in a state that would immediately collapse when a single untrustworthy agent would be re-introduced. Only when R >= 27 some simulations end in situations of high payoffs for the network without the complete absence of UC players. This same rule also gives issues in some highly connected and dense structures, but then because TC (or TP) completely disappears from the network before the strategy distribution is 'friendly' enough for them to flourish. This shows that the update rule chosen by Chica et. al. (2017) might not be suitable in a certain part of the reward space. A possible solution for this will be discussed in section V.

In general, community structure, compared to complete randomness and other structures (not covered in tables) spread the risk of a run, as a portfolio of different gambles. Even in low payoffs, one community can develop a situation of trust, which will always spread as long as other communities are neutral enough. Neutral in this context means having a majority of UP players, which TP and TC do not lead significant losses against. Community structure can also protect the network: if one community has an 'outbreak' of opportunism, depending on the other factors, it can be 'dealt with' within the community, i.e, walk through the Balancing effect on a small scale, while not influencing the rest of the network.

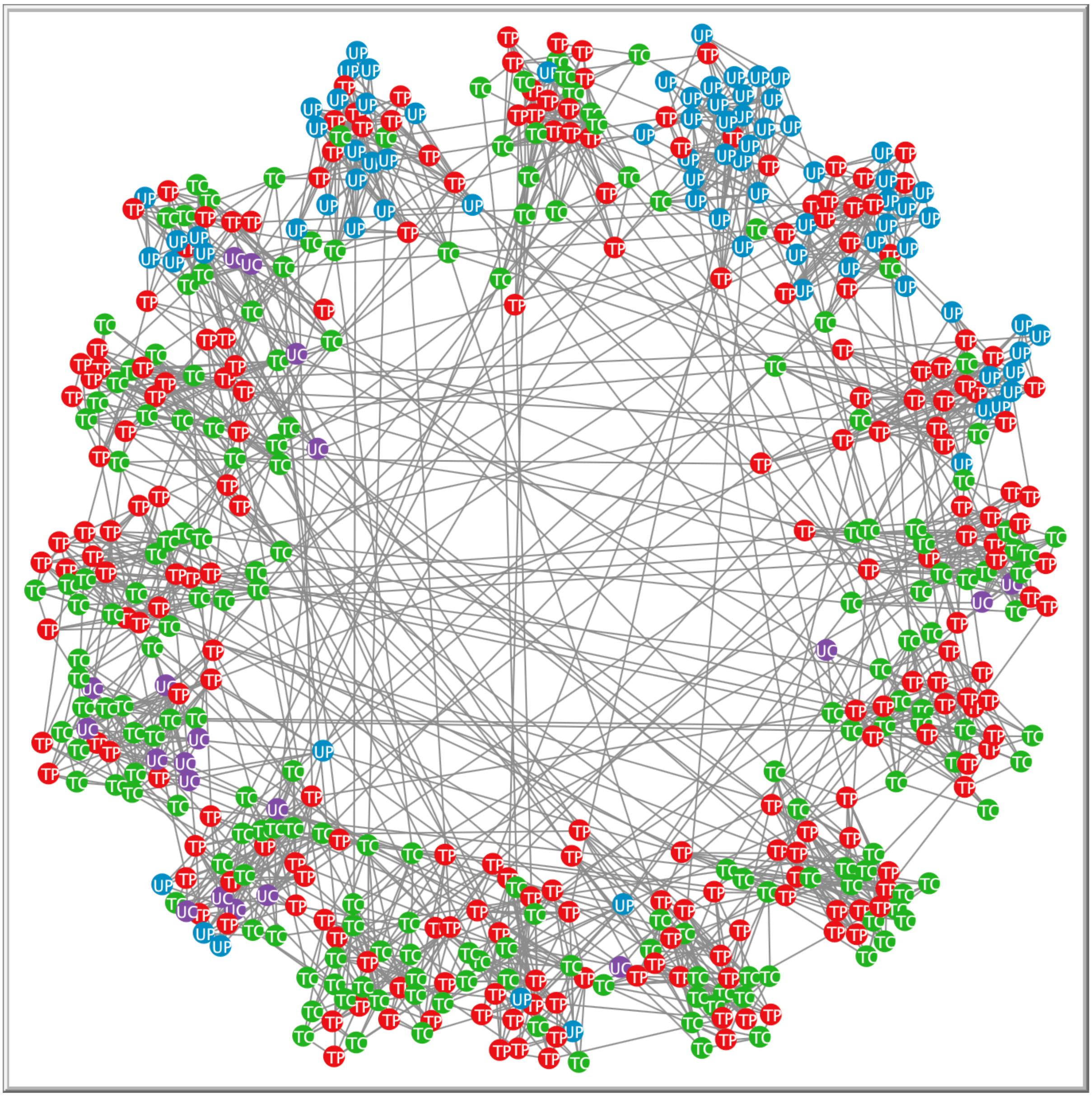

*Figure 3.* An example network visualisation in which the effect of community separation is visible (D = 8, P = 0.05, R = 30, time-step = 250).

| 21 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1055 | 1088 | 1286 | 1146 | 1215 | 1027 | 1158 | 772 | 872 | 907 | 942 |
| 6 | 1086 | 1042 | 984 | 869 | 874 | 793 | 827 | 743 | 550 | 669 | 553 |
| 8 | 839 | 796 | 857 | 712 | 917 | 789 | 635 | 273 | 424 | 349 | 237 |
| 10 | 465 | 791 | 856 | 631 | 827 | 679 | 476 | 265 | 192 | 244 | 156 |
| 12 | 282 | 483 | 421 | 580 | 627 | 396 | 126 | 80 | 44 | 7 | 44 |
| 14 | 177 | 116 | 415 | 275 | 426 | 277 | 120 | 82 | 7 | 77 | 44 |
| 16 | 134 | 45 | 235 | 197 | 119 | 83 | 273 | 8 | 8 | 8 | 9 |
| 18 | 110 | 113 | 45 | 44 | 122 | 195 | 83 | 77 | 79 | 46 | 8 |
| 20 | 129 | 44 | 80 | 190 | 8 | 122 | 48 | 9 | 9 | 8 | 8 |
| 22 | 9 | 39 | 43 | 76 | 9 | 11 | 44 | 11 | 10 | 10 | 10 |

| 24 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1473 | 1414 | 1507 | 1467 | 1347 | 1338 | 1376 | 1345 | 1256 | 1184 | 1237 |
| 6 | 1382 | 1460 | 1497 | 1515 | 1474 | 1430 | 1309 | 1225 | 1121 | 1210 | 1071 |
| 8 | 1271 | 1392 | 1362 | 1229 | 1327 | 1374 | 1230 | 1134 | 804 | 919 | 727 |
| 10 | 1288 | 930 | 1185 | 1173 | 1362 | 1129 | 1133 | 814 | 839 | 757 | 666 |
| 12 | 803 | 998 | 851 | 901 | 948 | 987 | 1031 | 352 | 660 | 610 | 532 |
| 14 | 734 | 561 | 878 | 712 | 807 | 713 | 717 | 611 | 389 | 347 | 303 |
| 16 | 208 | 591 | 528 | 226 | 487 | 579 | 535 | 387 | 219 | 261 | 212 |
| 18 | 284 | 264 | 350 | 354 | 452 | 400 | 437 | 94 | 130 | 8 | 52 |
| 20 | 159 | 89 | 350 | 265 | 228 | 352 | 307 | 9 | 48 | 8 | 53 |
| 22 | 79 | 124 | 203 | 86 | 243 | 292 | 120 | 125 | 9 | 8 | 86 |

| 27 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1757 | 1736 | 1738 | 1794 | 1747 | 1626 | 1694 | 1635 | 1685 | 1658 | 1558 |
| 6 | 1687 | 1600 | 1583 | 1305 | 1453 | 1438 | 1375 | 1548 | 1349 | 1557 | 1401 |
| 8 | 1591 | 1556 | 1514 | 1328 | 1540 | 1367 | 1366 | 1492 | 1472 | 1455 | 1406 |
| 10 | 1542 | 1499 | 1498 | 1599 | 1251 | 1381 | 1344 | 1518 | 1379 | 1531 | 1323 |
| 12 | 1161 | 1491 | 1380 | 1328 | 1427 | 1361 | 1191 | 1388 | 1160 | 1017 | 1280 |
| 14 | 1008 | 1134 | 1000 | 1205 | 1154 | 1316 | 1320 | 1010 | 1073 | 916 | 945 |
| 16 | 664 | 928 | 1095 | 950 | 801 | 892 | 1069 | 868 | 767 | 641 | 725 |
| 18 | 556 | 823 | 546 | 885 | 604 | 699 | 1073 | 819 | 574 | 385 | 582 |
| 20 | 314 | 757 | 591 | 252 | 772 | 856 | 732 | 422 | 472 | 383 | 399 |
| 22 | 585 | 304 | 223 | 519 | 532 | 352 | 643 | 222 | 292 | 259 | 253 |

| 30 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1961 | 1972 | 1922 | 1806 | 1670 | 1650 | 1324 | 1447 | 1450 | 1592 | 1539 |
| 6 | 1857 | 1371 | 1259 | 1274 | 984 | 994 | 837 | 1061 | 1314 | 1310 | 1185 |
| 8 | 1867 | 1495 | 1056 | 1148 | 868 | 1077 | 762 | 1007 | 974 | 897 | 1175 |
| 10 | 1878 | 1588 | 1238 | 1198 | 839 | 1088 | 904 | 968 | 940 | 1159 | 869 |
| 12 | 1756 | 1533 | 1270 | 1144 | 1023 | 1199 | 783 | 1062 | 1135 | 1044 | 1023 |
| 14 | 1504 | 1534 | 1320 | 1394 | 1248 | 922 | 846 | 1324 | 1075 | 1250 | 882 |
| 16 | 1365 | 1493 | 1156 | 1339 | 972 | 790 | 1025 | 1229 | 1137 | 1093 | 1103 |
| 18 | 1016 | 1339 | 1252 | 805 | 1099 | 1026 | 883 | 1137 | 966 | 1226 | 1355 |
| 20 | 1008 | 939 | 1204 | 768 | 1026 | 1208 | 855 | 1139 | 870 | 781 | 1112 |
| 22 | 503 | 775 | 874 | 964 | 897 | 1338 | 954 | 902 | 753 | 921 | 685 |

| 33 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 2207 | 2173 | 2230 | 2160 | 2199 | 2076 | 1903 | 1566 | 1607 | 1552 | 1585 |
| 6 | 2169 | 2117 | 1631 | 1461 | 1363 | 1216 | 1029 | 928 | 924 | 1094 | 946 |
| 8 | 2027 | 1833 | 1136 | 1087 | 927 | 979 | 884 | 858 | 892 | 928 | 909 |
| 10 | 2046 | 1679 | 950 | 934 | 805 | 791 | 865 | 761 | 781 | 767 | 750 |
| 12 | 1777 | 1687 | 848 | 902 | 770 | 753 | 815 | 792 | 853 | 672 | 872 |
| 14 | 1918 | 1787 | 963 | 856 | 680 | 853 | 824 | 684 | 783 | 740 | 689 |
| 16 | 1620 | 1688 | 1092 | 750 | 697 | 649 | 773 | 626 | 752 | 823 | 738 |
| 18 | 1643 | 1600 | 1106 | 838 | 893 | 596 | 678 | 687 | 703 | 780 | 689 |
| 20 | 1322 | 1432 | 1294 | 1041 | 859 | 747 | 647 | 794 | 970 | 818 | 872 |
| 22 | 1182 | 1314 | 1010 | 1015 | 763 | 557 | 572 | 635 | 616 | 803 | 746 |

| 36 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 2451 | 2461 | 2466 | 2450 | 2464 | 2452 | 2425 | 2389 | 2361 | 2336 | 2332 |
| 6 | 2533 | 2539 | 2556 | 2554 | 2545 | 2527 | 2491 | 2414 | 2420 | 2430 | 2433 |
| 8 | 2508 | 2530 | 2535 | 2532 | 2517 | 2512 | 2466 | 2346 | 2348 | 2300 | 2327 |
| 10 | 2470 | 2475 | 2503 | 2480 | 2484 | 2474 | 2393 | 2165 | 2137 | 2171 | 2044 |
| 12 | 2389 | 2417 | 2430 | 2428 | 2421 | 2401 | 2251 | 1954 | 1908 | 1931 | 1893 |
| 14 | 2317 | 2341 | 2358 | 2331 | 2266 | 2268 | 2129 | 1796 | 1718 | 1688 | 1740 |
| 16 | 2164 | 2250 | 2187 | 2249 | 2160 | 2037 | 1885 | 1648 | 1594 | 1558 | 1553 |
| 18 | 2206 | 2158 | 2088 | 1987 | 1922 | 1900 | 1700 | 1505 | 1491 | 1416 | 1425 |
| 20 | 1908 | 2001 | 1847 | 1822 | 1699 | 1681 | 1558 | 1423 | 1332 | 1328 | 1298 |
| 22 | 1941 | 1814 | 1620 | 1599 | 1504 | 1466 | 1453 | 1310 | 1254 | 1205 | 1244 |

| 39 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 2668 | 2668 | 2669 | 2681 | 2676 | 2670 | 2648 | 2609 | 2597 | 2559 | 2557 |
| 6 | 2776 | 2790 | 2793 | 2804 | 2793 | 2792 | 2782 | 2770 | 2755 | 2741 | 2746 |
| 8 | 2779 | 2786 | 2798 | 2797 | 2799 | 2791 | 2791 | 2790 | 2788 | 2777 | 2778 |
| 10 | 2755 | 2772 | 2773 | 2773 | 2775 | 2779 | 2785 | 2783 | 2776 | 2777 | 2773 |
| 12 | 2719 | 2741 | 2745 | 2749 | 2759 | 2759 | 2764 | 2769 | 2767 | 2763 | 2758 |
| 14 | 2695 | 2704 | 2720 | 2730 | 2724 | 2733 | 2745 | 2753 | 2750 | 2742 | 2749 |
| 16 | 2658 | 2682 | 2688 | 2692 | 2700 | 2710 | 2727 | 2730 | 2723 | 2724 | 2735 |
| 18 | 2624 | 2648 | 2669 | 2670 | 2689 | 2690 | 2701 | 2717 | 2712 | 2714 | 2717 |
| 20 | 2596 | 2621 | 2632 | 2650 | 2665 | 2672 | 2691 | 2695 | 2692 | 2701 | 2696 |
| 22 | 2572 | 2589 | 2614 | 2621 | 2642 | 2654 | 2673 | 2687 | 2681 | 2683 | 2679 |


| 21 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1055 | 1088 | 1286 | 1146 | 1215 | 1027 | 1158 | 772 | 872 | 907 | 942 |
| 6 | 1086 | 1042 | 984 | 869 | 874 | 793 | 827 | 743 | 550 | 669 | 553 |
| 8 | 839 | 796 | 857 | 712 | 917 | 789 | 635 | 273 | 424 | 349 | 237 |
| 10 | 465 | 791 | 856 | 631 | 827 | 679 | 476 | 265 | 192 | 244 | 156 |
| 12 | 282 | 483 | 421 | 580 | 627 | 396 | 126 | 80 | 44 | 7 | 44 |
| 14 | 177 | 116 | 415 | 275 | 426 | 277 | 120 | 82 | 7 | 77 | 44 |
| 16 | 134 | 45 | 235 | 197 | 119 | 83 | 273 | 8 | 8 | 8 | 9 |
| 18 | 110 | 113 | 45 | 44 | 122 | 195 | 83 | 77 | 79 | 46 | 8 |
| 20 | 129 | 44 | 80 | 190 | 8 | 122 | 48 | 9 | 9 | 8 | 8 |
| 22 | 9 | 39 | 43 | 76 | 9 | 11 | 44 | 11 | 10 | 10 | 10 |

| 24 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1473 | 1414 | 1507 | 1467 | 1347 | 1338 | 1376 | 1345 | 1256 | 1184 | 1237 |
| 6 | 1382 | 1460 | 1497 | 1515 | 1474 | 1430 | 1309 | 1225 | 1121 | 1210 | 1071 |
| 8 | 1271 | 1392 | 1362 | 1229 | 1327 | 1374 | 1230 | 1134 | 804 | 919 | 727 |
| 10 | 1288 | 930 | 1185 | 1173 | 1362 | 1129 | 1133 | 814 | 839 | 757 | 666 |
| 12 | 803 | 998 | 851 | 901 | 948 | 987 | 1031 | 352 | 660 | 610 | 532 |
| 14 | 734 | 561 | 878 | 712 | 807 | 713 | 717 | 611 | 389 | 347 | 303 |
| 16 | 208 | 591 | 528 | 226 | 487 | 579 | 535 | 387 | 219 | 261 | 212 |
| 18 | 284 | 264 | 350 | 354 | 452 | 400 | 437 | 94 | 130 | 8 | 52 |
| 20 | 159 | 89 | 350 | 265 | 228 | 352 | 307 | 9 | 48 | 8 | 53 |
| 22 | 79 | 124 | 203 | 86 | 243 | 292 | 120 | 125 | 9 | 8 | 86 |

| 27 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1757 | 1736 | 1738 | 1794 | 1747 | 1626 | 1694 | 1635 | 1685 | 1658 | 1558 |
| 6 | 1687 | 1600 | 1583 | 1305 | 1453 | 1438 | 1375 | 1548 | 1349 | 1557 | 1401 |
| 8 | 1591 | 1556 | 1514 | 1328 | 1540 | 1367 | 1366 | 1492 | 1472 | 1455 | 1406 |
| 10 | 1542 | 1499 | 1498 | 1599 | 1251 | 1381 | 1344 | 1518 | 1379 | 1531 | 1323 |
| 12 | 1161 | 1491 | 1380 | 1328 | 1427 | 1361 | 1191 | 1388 | 1160 | 1017 | 1280 |
| 14 | 1008 | 1134 | 1000 | 1205 | 1154 | 1316 | 1320 | 1010 | 1073 | 916 | 945 |
| 16 | 664 | 928 | 1095 | 950 | 801 | 892 | 1069 | 868 | 767 | 641 | 725 |
| 18 | 556 | 823 | 546 | 885 | 604 | 699 | 1073 | 819 | 574 | 385 | 582 |
| 20 | 314 | 757 | 591 | 252 | 772 | 856 | 732 | 422 | 472 | 383 | 399 |
| 22 | 585 | 304 | 223 | 519 | 532 | 352 | 643 | 222 | 292 | 259 | 253 |

| 30 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1961 | 1972 | 1922 | 1806 | 1670 | 1650 | 1324 | 1447 | 1450 | 1592 | 1539 |
| 6 | 1857 | 1371 | 1259 | 1274 | 984 | 994 | 837 | 1061 | 1314 | 1310 | 1185 |
| 8 | 1867 | 1495 | 1056 | 1148 | 868 | 1077 | 762 | 1007 | 974 | 897 | 1175 |
| 10 | 1878 | 1588 | 1238 | 1198 | 839 | 1088 | 904 | 968 | 940 | 1159 | 869 |
| 12 | 1756 | 1533 | 1270 | 1144 | 1023 | 1199 | 783 | 1062 | 1135 | 1044 | 1023 |
| 14 | 1504 | 1534 | 1320 | 1394 | 1248 | 922 | 846 | 1324 | 1075 | 1250 | 882 |
| 16 | 1365 | 1493 | 1156 | 1339 | 972 | 790 | 1025 | 1229 | 1137 | 1093 | 1103 |
| 18 | 1016 | 1339 | 1252 | 805 | 1099 | 1026 | 883 | 1137 | 966 | 1226 | 1355 |
| 20 | 1008 | 939 | 1204 | 768 | 1026 | 1208 | 855 | 1139 | 870 | 781 | 1112 |
| 22 | 503 | 775 | 874 | 964 | 897 | 1338 | 954 | 902 | 753 | 921 | 685 |

| 33 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 2207 | 2173 | 2230 | 2160 | 2199 | 2076 | 1903 | 1566 | 1607 | 1552 | 1585 |
| 6 | 2169 | 2117 | 1631 | 1461 | 1363 | 1216 | 1029 | 928 | 924 | 1094 | 946 |
| 8 | 2027 | 1833 | 1136 | 1087 | 927 | 979 | 884 | 858 | 892 | 928 | 909 |
| 10 | 2046 | 1679 | 950 | 934 | 805 | 791 | 865 | 761 | 781 | 767 | 750 |
| 12 | 1777 | 1687 | 848 | 902 | 770 | 753 | 815 | 792 | 853 | 672 | 872 |
| 14 | 1918 | 1787 | 963 | 856 | 680 | 853 | 824 | 684 | 783 | 740 | 689 |
| 16 | 1620 | 1688 | 1092 | 750 | 697 | 649 | 773 | 626 | 752 | 823 | 738 |
| 18 | 1643 | 1600 | 1106 | 838 | 893 | 596 | 678 | 687 | 703 | 780 | 689 |
| 20 | 1322 | 1432 | 1294 | 1041 | 859 | 747 | 647 | 794 | 970 | 818 | 872 |
| 22 | 1182 | 1314 | 1010 | 1015 | 763 | 557 | 572 | 635 | 616 | 803 | 746 |

| 36 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 2451 | 2461 | 2466 | 2450 | 2464 | 2452 | 2425 | 2389 | 2361 | 2336 | 2332 |
| 6 | 2533 | 2539 | 2556 | 2554 | 2545 | 2527 | 2491 | 2414 | 2420 | 2430 | 2433 |
| 8 | 2508 | 2530 | 2535 | 2532 | 2517 | 2512 | 2466 | 2346 | 2348 | 2300 | 2327 |
| 10 | 2470 | 2475 | 2503 | 2480 | 2484 | 2474 | 2393 | 2165 | 2137 | 2171 | 2044 |
| 12 | 2389 | 2417 | 2430 | 2428 | 2421 | 2401 | 2251 | 1954 | 1908 | 1931 | 1893 |
| 14 | 2317 | 2341 | 2358 | 2331 | 2266 | 2268 | 2129 | 1796 | 1718 | 1688 | 1740 |
| 16 | 2164 | 2250 | 2187 | 2249 | 2160 | 2037 | 1885 | 1648 | 1594 | 1558 | 1553 |
| 18 | 2206 | 2158 | 2088 | 1987 | 1922 | 1900 | 1700 | 1505 | 1491 | 1416 | 1425 |
| 20 | 1908 | 2001 | 1847 | 1822 | 1699 | 1681 | 1558 | 1423 | 1332 | 1328 | 1298 |
| 22 | 1941 | 1814 | 1620 | 1599 | 1504 | 1466 | 1453 | 1310 | 1254 | 1205 | 1244 |

| 39 | 0.01 | 0.02 | 0.04 | 0.05 | 0.08 | 0.1 | 0.2 | 0.4 | 0.5 | 0.8 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 2668 | 2668 | 2669 | 2681 | 2676 | 2670 | 2648 | 2609 | 2597 | 2559 | 2557 |
| 6 | 2776 | 2790 | 2793 | 2804 | 2793 | 2792 | 2782 | 2770 | 2755 | 2741 | 2746 |
| 8 | 2779 | 2786 | 2798 | 2797 | 2799 | 2791 | 2791 | 2790 | 2788 | 2777 | 2778 |
| 10 | 2755 | 2772 | 2773 | 2773 | 2775 | 2779 | 2785 | 2783 | 2776 | 2777 | 2773 |
| 12 | 2719 | 2741 | 2745 | 2749 | 2759 | 2759 | 2764 | 2769 | 2767 | 2763 | 2758 |
| 14 | 2695 | 2704 | 2720 | 2730 | 2724 | 2733 | 2745 | 2753 | 2750 | 2742 | 2749 |
| 16 | 2658 | 2682 | 2688 | 2692 | 2700 | 2710 | 2727 | 2730 | 2723 | 2724 | 2735 |
| 18 | 2624 | 2648 | 2669 | 2670 | 2689 | 2690 | 2701 | 2717 | 2712 | 2714 | 2717 |
| 20 | 2596 | 2621 | 2632 | 2650 | 2665 | 2672 | 2691 | 2695 | 2692 | 2701 | 2696 |
| 22 | 2572 | 2589 | 2614 | 2621 | 2642 | 2654 | 2673 | 2687 | 2681 | 2683 | 2679 |


*Figure 4.* Observed average payoffs for a specific combination of degree D (y-axis) and rewiring P (x-axis), grouped in blocks by reward value (value in upper-left corner of each block). The reported numbers are the average payoffs of all agents together (in millions), over at least 32 runs, coloured relative to the other results with the same reward R (left) or relative to all results (right).

**Analysis of end states.** Observed average payoffs for a specific combination of degree D (y-axis) and rewiring P (x-axis), grouped in blocks by reward value (upper-left corner of each block). The reported numbers are the average payoffs of all agents together (in millions), over at least 32 runs, coloured relative to the other results with the same reward R (left) or relative to all results (right).

In figure 4, the observed average payoffs for a specific combination of degree D (Y-axis) and rewiring P (X-axis) are shown, grouped in blocks by reward value. The reported numbers are coloured relative to the other results with the same value for R (left) or relative to all results (right). Higher average payoffs indicate a network had many agents with TC and TP strategies trading with each other. End states with a degree of 2 were omitted because the network was too often split up in multiple networks by rewiring. Networks splitting was also an issue at D = 4, where total payoffs are lower because disconnected agents did not always have a trading partner. This is most clearly visible in the tables when the reward is equal to 39.

In the tables, especially the right-hand table where colour is relative to all achieved payoffs, patterns related to the three variables can be visually identified: In all reward spaces, degree seems to have a negative correlation with the total average payoff. Secondly, a negative correlation to the level of rewiring can be distinguished, most clearly in the moderate-high reward areas. Thirdly, higher rewards expectedly led to higher payoffs, but at R = 39 the interaction with degree and rewiring suddenly changes, as is visible in the left-hand column of tables. The last part of this analysis will dive into these three patterns in more detail.

Looking at the role of degree in more detail, we see a consistent effect at the level of the individual agent. A high value for D makes it harder for trustworthy behaviour to survive in thesimulations. As soon as an UC is able to reach one or more TP's, their opportunistic behaviour can quickly spread. A lower number of edges means UC's cannot spread as effective, and have a higher likelihood of being stopped somewhere either by 'running into' a group of UP's, or by not being able to spread to a node because it is highly successful in its trade with other trusting and trustworthy agents.

The effect of rewiring seems to depend highly on the value of R, i.e., how ‘hard’ the game is. For low rewards, higher connectedness makes for quicker extinctions, which is the only way to success (if UC goes extinct) or failure (when TC or TP goes extinct) for this area of variables. In figure 5, two runs with the same setup conditions are shown, to illustrate the two only occurring courses of a simulation in this variable space. The complete dependence on the extinction of UC is a risky dynamic for reaching a situation of complete trust, but apparently, it is not influenced much by the structural specifics, mostly just the randomness in the initial placement of strategies and the element of chance in the strategy selection. This area should not be considered for real-world implications since this extinction-dependency might be very unrealistic.

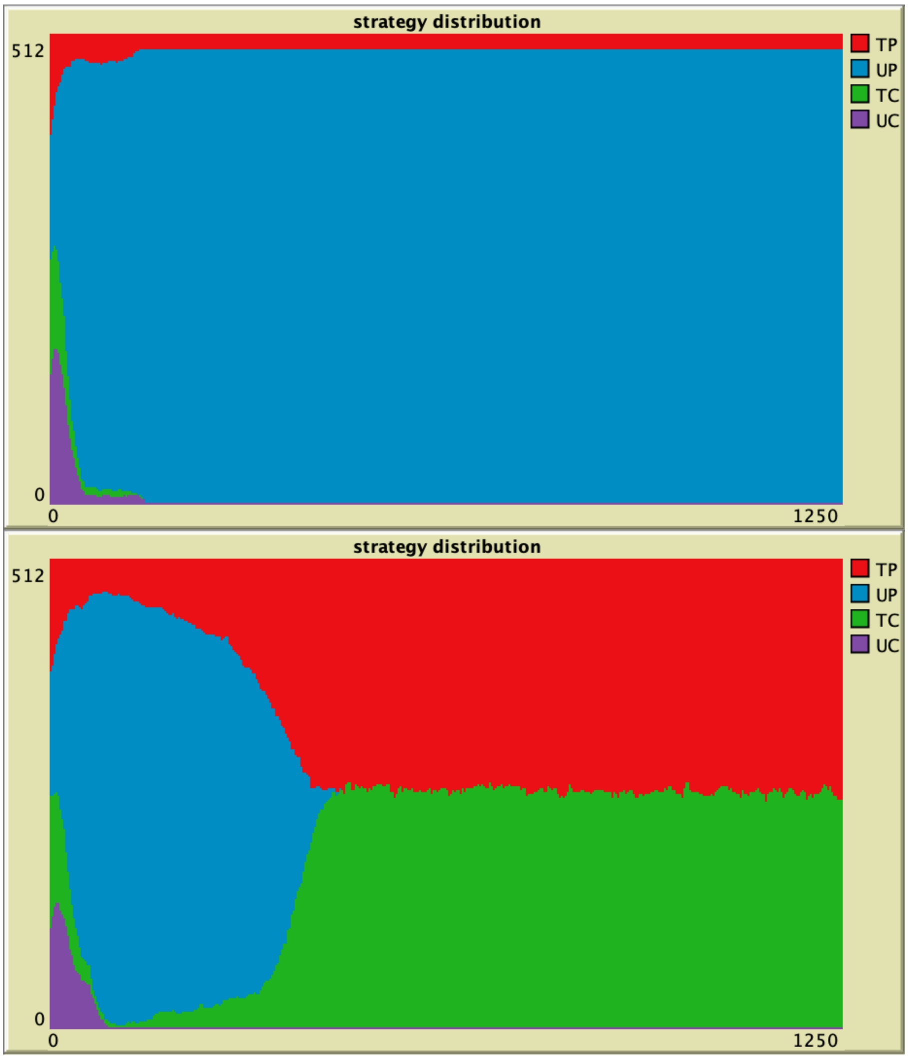


*Figure 5.* The two occurring courses of a simulation in the low reward-space (D = 16, P = 0.01, R = 24).


*Figure 6.* The visible chaos in moderate reward values for three different amounts of rewiring from low to high (D = 16, P = 0.01 (top) 0.1 (middle) 1 (bottom), R = 24).

For medium values of R, the situations become more chaotic, and rewiring seems to increase this chaos. The network does not go through the balancing effect as a whole since some communities can be thriving purely based on higher payoffs if the amount of trust is high from the start by random assignment. Because higher rewards make complete extinction of UC no longer a necessity, communities can have successful interactions before the rest of the network does. Balancing happens locally, which makes the structure more important. This clear distinction for medium rewards might explain some of the results observed by Chica et al. (2017) around an R of 27, where end states seemed to be inconsistent with other trends. When communities are not very connected, they will find a stable situation on their own, often by complete extinction of UC. The fact that communities change independent of others is visible in the top pattern in fig. 6, where fluctuations are in steps of 1/16th of the Y axis, corresponding to one or more communities at a time. When a community is thriving, the low connectedness makes for a protected situation where opportunistic behaviour cannot reach the community. In more connected communities, UC's from a single community can repeatedly spread towards other communities. This, combined with the fact that communities started to thrive before UC went extinct, causes continuous fluctuations in strategies across the network.

In the situation of high rewards, the effect of rewiring becomes more predictable. The 'easy' nature of the game causes the payoffs gained by trusting and trustworthy behaviour to be the primary driver of success, without much need for the balancing dynamic for the whole network. Less rewiring benefits the development of trust by making individual communities 'find' the quickest way to success for them. It seems as though the separation of the network makes this more efficient because each community goes through the dynamic that is relevant for their initial distribution of strategies: sometimes a quick balancing dynamic, or a slower decrease of opportunistic behaviour via higher payoffs gained by TP and TC if possible. Because the network does not have to do this as a whole, it is quicker.

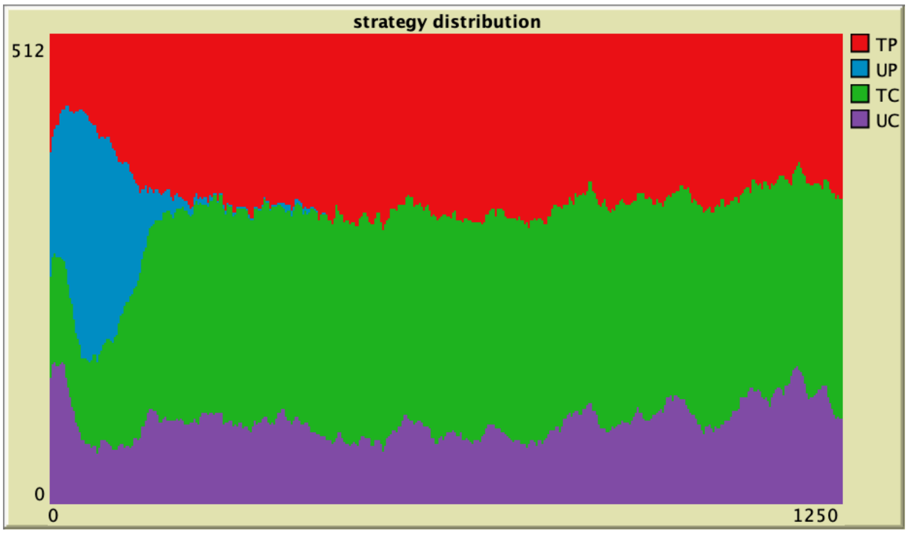


*Figure 7.* A typical simulation run in with high rewards, with only a small balancing dynamic visible, and an equilibrium with UC agents present (D = 16, P = 0.1, R = 36).

A seemingly strange pattern is observed when looking at the table for R = 39 in the left-hand column, where payoffs are coloured relative to the other average payoffs with the same reward. The pattern seems to have 'flipped' on the rewiring axis, compared to the tables for other reward values.[7] When observing the right-hand version, it can be seen that these differences are minimal, and not noticeable relative to other reward values. Looking at some simulations in more detail, the following explanation can be found: both reasoning about extinction or protection by the community do not apply here. The game is in favour of agents with a strategies of trust to the point that the only important thing is how fast these strategies can spread. Confirming to dynamics described in the very first paper on small-world networks by Watts & Strogatz (1998), signal propagation is quicker on networks approaching random networks.

## Concluding Remarks and Future Work

This paper built upon the novel evolutionary trust game from Chica et al. (2017) by adding the dimension of network structure, specifically average degree and connectedness between communities in a community network. It has become clear

[7] The low payoffs at D = 4 are because of parts of the network disconnecting when rewired, as mentioned at the beginning of this section.

that the network structure can have substantial effects on the success of a sharing economy network. Additionally, it was found that the rewards in the game do not only influence end states, but also influence dynamics and the effect of other variables. Clearly, this type of exploration cannot be done with many variables kept constant. Because of the strong interactions between variables, exact quantification of interaction is necessary. The latter is currently impossible because of the lack of mathematical frameworks in this area.

The presented sharing economy trust model consists of 512 agents, arranged in 16 communities, where the degree and amount of edges rewired from inter-community to a random agent were systematically varied together with the reward for cooperation in the trust game. Each agent could choose to be a provider or consumer and to be trusting/trustworthy or not, evaluating every 50 games, simulating the evolution of chosen strategies over time.

These computational experiments suggested that more isolated communities could be a safe place to start the formation of trusting behaviour. It possibly also prevents opportunistic behaviour from spreading to the rest of the network quickly. In line with previous research on social dilemma-games, a higher number of individual connections makes an agent more vulnerable to opportunism, thereby decreasing the total payoffs for the network when the average degree is higher. Looking at the effect of community connectedness, it was discovered that the simulation is especially sensitive to the amount of rewiring in the lower rewiring values. The effects of this variable turned out to be highly dependent on the chosen reward in the trust game. As expected, higher rewards in the trust game create resilience to opportunistic behaviour, independent of other variables.

The balancing effect discovered by Chica et al. (2017) was present in many of the simulations and was essential to the development of successful interactions when rewards were low. This occurrence of the dynamic does, however, create the unrealistic situation of complete extinction of strategies, which deteriorates their game's real-world application value. This problem became visible because of the visual user-interface available in this paper's simulation.

Although the value of this application to the sharing economy is mainly in the advancement of knowledge about the used theoretical frameworks by finding their limitations in these situations, some of the results could be extrapolated to findings relevant for sharing economy platforms. Firstly, it is important for platforms to know how 'hard' their interactions are. In the case that transactions are high in risk, it could be beneficial to limit the amount of different people an individual can interact with at first. When the benefits of a platform are obvious, and risks are low, the platform could benefit from bringing together people who wouldn't normally do so, to effectively create bridges in the network. Secondly, this research suggests that fostering the community structure of a platform could be beneficial. Often, platforms serve a user with multiple possible providers to have a transaction with, and a 'recommender system' decides which options to show you first (Grbovic, 2017). Since recommendation algorithms include deliberate choices by the platform, it can be used to influence the structure of the occurring transactions network. Another possibility is explicitly highlighting characteristics of the underlying network structure to the user (e.g., friends in common, others you both had a transaction with), to increase the level of trust, like Airbnb is already doing (Airbnb 2011).

This thesis is part of the balance that has to be found between developing theoretical frameworks on the one hand, while applications on the other hand do not have to wait until the theory is fully mature, so they can drive the theory forward. Especially agent-based simulations with a GUI, like the one used here, can have a big educational value. This does, however, mean that some limitations have to be considered when interpreting the results. For network structure, it is unknown what actual networks of possible interactions look like, or how they relate to the observable networks of occurring transactions. The number of transactions of agents might very well follow a power-law distribution in terms of weight or centrality (Teubner, 2017). Other network structures could also include a more rigid distinction between players who can provide an asset and those who cannot, or the possibility for players to create or delete links between them, creating a dynamic graph (Rand, Arbesman, & Christakis, 2011). These options can be considered for future research.

Considering the other components of the game, the chosen game structure and evolution rule might not be the best abstract representation of reality. This paper's findings highlight a major issue with the proportional imitation rule: the fact that strategies can completely disappear from the simulated world, a very unrealistic situation. There exists a trade-off between simplicity and realism, but a simple way to address this issue would be the introduction of noise to the simulation: a small chance of random mutation for each agent. Other alternatives that can be considered include evaluation rules in which agents memorise previous payoffs and strategies, either increasing knowledge about their past state or the network as a whole.

This thesis also presented a unique way of reporting data in a multidimensional behaviour-space, using heat maps to find areas of interest in an abundance of data. With the computing power of current consumer hardware, ABM provides a way to generate amounts of data previously impossible without high-performance computing clusters (and therefore seldom viable). This requires new ways of interpreting and visualising results. Future possibilities for this kind of research include generating data including even more variables. Artificial intelligence and other methods from so-called 'big data' research could be used to find patterns and dynamics. Taking this even further, simulation as a method could be developed into a complete representation of both micro- and macroeconomics, creating a form of Agent-Based Computational Economics (Tesfatsion, 2002).

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## Appendix A

The structure of the simulation and some of the specificities are from the ABED-1pop framework (Izquierdo, Izquierdo, & Sandholm, 2018), published under the GNU General Public License. The network statistics and layout procedures are from a code snippet sent by Luis R. Izquierdo, whom I would like to thank for his encouragement and helpful directions at the start of my programming endeavour. Many of the methods and my general ability to program in NetLogo came from the book "Agent-Based Evolutionary Game Dynamics" by Izquierdo, Izquierdo, & Sandholm (in press). The code is specific to its application, and readability was often prioritised over flexibility. No warranty of merchantability or fitness for a particular purpose is implied.

The GUI is further explained below:

A. The network settings. Only community structure is used in this paper, but some of NetLogo's build in structures like the Small-World network are also available. With sliders, he number of nodes, the average degree and the probability for rewiring can be changed.

B. Community settings. Including the number of communities and whether or not they should always be connected. This optional procedure makes sure all the communities have at least one link to another community, even when the community connectedness is zero. This is used in all the simulations in this paper, to present results about one single network and prevent changes in network size across variations of the other variables. This does, however, rewire additional edges, resulting in an increase in intra-community edges corresponding to an increase of the effective connectedness between 0.0002 and 0.004 for the presented experimental setup.

C. Payoff settings. Reward can be varied with a slider, all other payoffs can also manually be adjusted in the 4x4 array.

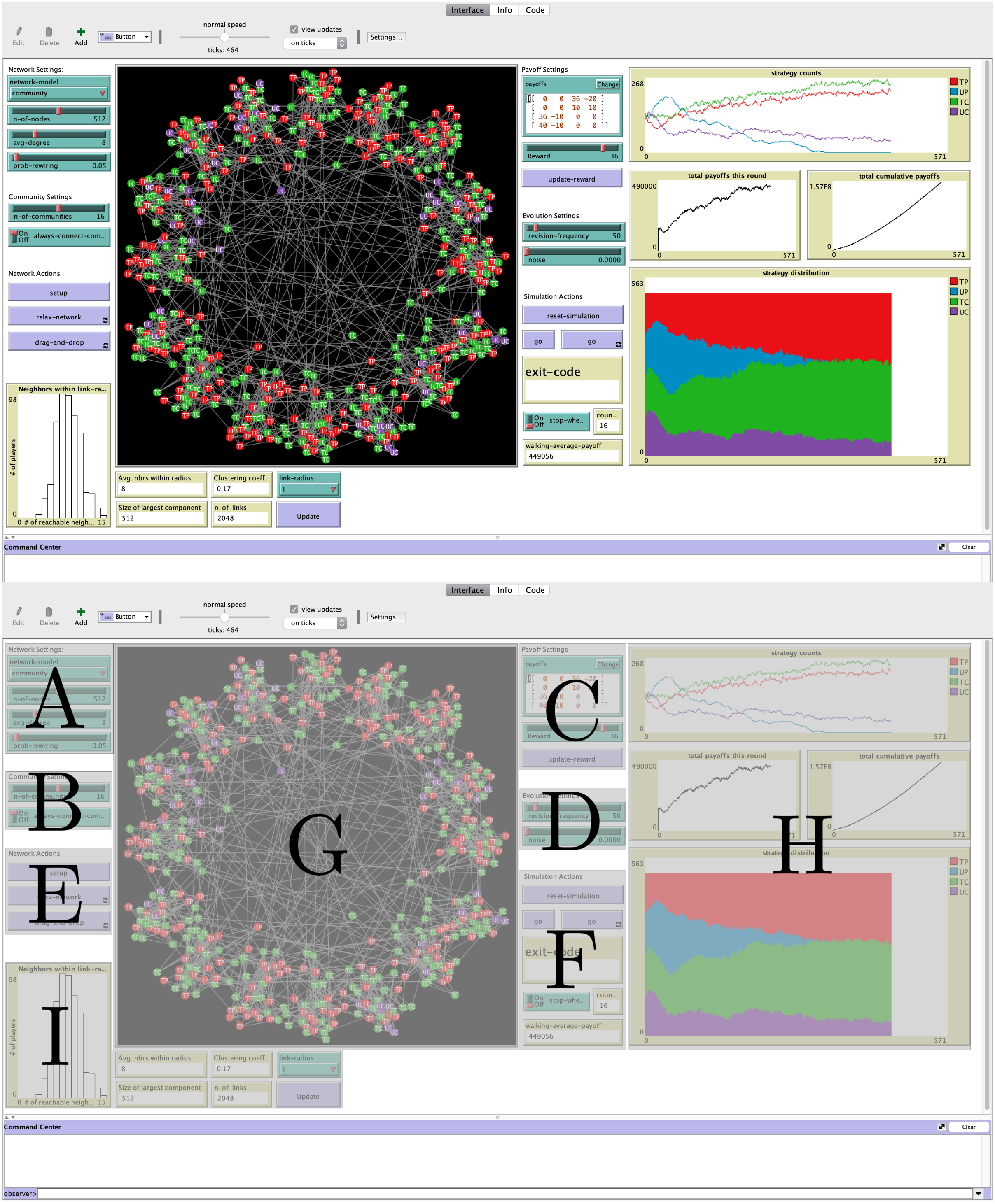


*Figure 7.* An overview of the GUI developed and used for this paper's simulations.

D. Network actions. Setup sets the initial network up in a basic layout, which can be further adjusted by 'relaxing' the network or manually by dragging and dropping nodes. The relax-network procedure makes nodes move according to their amount of edges and how far the connected nodes are away, creating an organic looking layout.

E. Simulation actions. To start the situation continuously or watch it step by step. A simulation can also be reset without changing the network. The 'exit-code' reports if a network has reached a stable state (no-trust or only-trust). While gathering of data, a simulation was only run for 16 more steps after reaching a stable state to save time. 16 more steps was found to be enough to estimate the payoffs for the rest of the simulation, since they merely fluctuating around a mean after an equilibrium has been reached.

F. The main visualisation. Nodes have a colour and label corresponding to their strategy, all visually updated after every strategy evaluation. This is what made this program unique, and enabled in depth visual inspection of occurring dynamics. With the 'say-cheese' procedure, nodes can be coloured by community, and put agains a white background, better for taking screenshots.

G. Reporters of strategy quantity and payoffs gained. The upper graph reports the presence of strategies, the bottom one does the same, but in a clearer stacked bar chart. Payoffs during a round and cumulative payoffs are reported to see changes in 'success' over time. All graphs automatically adjust their scale to fit the data or can have fixed dimensions to export screenshots.

H. Reporters about the network structure. This includes the actual degree, degree distribution, clustering coefficient, wether or not a network was split up and the total number of links. Statistics about the nodes reached within one or more degrees of separation can be seen by adjusting the link radius for which the statistics are calculated.