From Agents to Large Actors and back

Formalized story-telling of emergence and exit in political economy

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Abstract

This paper presents a simulation model that is capable to explore essential features of the emergence and exit of economic institutions. The models used at the micro-level as well as the interactions which lead to the emergence of macro-behavior are described in detail, possible extensions are hinted at. With a large amount of simulation runs a classification of results is attempted, which enables to draw some conclusions from the implications of the chosen setting. Finally a few issues in political economy are brought into relation to the simulation framework provided.

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1. Introduction

The lifetime of all life forms that can be observed is finite. Birth and death, entry and exit are among the most common phenomena we encounter. Surprisingly enough theory building of the economic mainstream has stubbornly ignored these two basic elements of all living entities – at least for the last 100 years or so. Theories of the evolution of political economy remained curious and spurious outsiders, considered as Schumpeterean after-dinner-talks or artefacts owed to an unwise choice of axioms. Disregarding mainstream economic theory, economic reality in this last 100 years was characterized by emergence and exit of ever larger political entities. The contemporary global economy is best described as consisting of a few, heterogeneous, continental blocks, which in turn are linked by the activities of a somewhat larger group of global corporations. Of course, with higher granularity almost *self-similar structures and processes* of this type can be discovered within each of these blocks. The science of political economy thus clearly is forced by its object of investigation to produce an archetype of a model that can take care of entry and exit of the entities it describes[2].

'Natura non facit saltus', Leibniz and other natural scientists proclaimed a long time ago – and though modern quantum theory proved him deadly wrong even on his own grounds of nonliving matter already at the beginning of the last century, there still is the widespread believe that imitating outdated formalisms of physics could enhance economic theory. In this paper a modest attempt to formalize 'jumps of nature' - the sudden emergence, the unexpected death of social entities – is made. Such an attempt understandably needs new and different tools for formalization, and we thus propose agent based simulation techniques. The capability of a formalization tool is never independent of the object that it is used to deal with. The intellectual instrument evolves with the features of subject it is designed to master; with a

radical shift of focus, the most fine-tuned instruments become the most obsolete and blunt tools – e.g. general equilibrium analysis. As already argued above (and in a previous paper, see Radax, Wäckerle and Hanappi 2007) what currently is needed is a radical shift of focus in economics, namely a turn to political economy.

The choice of agent based computational modelling (ABM) as formalization tool is rather obvious: it is the only game in town, which combines the capacity to include the enormously increasing amount of empirical data and at the same time to be still a rigid mechanism forcing scientists to spell out in detail what is proposed as a model of reality. As should become clear

[2] In this respect mainstream economic theory usually takes the easy way out: the physical, individual, human persons on with which their theory is ‚micro-founded' are seen as biological entities – and the finiteness of their lifetime therefore luckily has to be handled by this other science department.

below, this splendid feature unfortunately has the consequence that this type of formalized story-telling gives the impression of an excessive amount of arbitrariness when compared to what was called an 'elegant' mathematical solution in old-style, high-brow mathematical economics. But aesthetic prejudice is going to change too, when applicability and urgent economic policy consulting is calling – at least this is our prejudice.

What are thus the cornerstones of the new approach? On the one hand it is the evolution of a heterogeneous set of entities, which entertain private internal models of the world in which they live. On the other hand it is the model of the real economic world in which they are connected by specific (and again heterogeneous) links of the activities that they decide to perform – in turn guided by their internal models. In particular the use of simulations with a manageably large amount of heterogeneous agents proves to be a good starting point. The next chapter will present a fresh framework which is able to handle a prototype of the emergent-entity-process in political economy. Therefore, at this point we give only a brief overview.

We propose a framework to model the emergence and exit of large entities in a political economy based on the interactions of individuals on the micro-level: The idea is to start with a micro setup within a specific space which represents the political economy – this space can be interpreted either as geographical or as social space. Agents populate this space and interact with each other locally. The interaction is based on a Prisoner's Dilemma logic, i.e. in every time step agents play the Prisoner's Dilemma game with their neighbors. According to the logic of the ordinary 2x2 Prisoner's Dilemma agents can either cooperate or defect. In our model agents are endowed with cognitive capabilities (a memory of events in the recent past, and a decision mechanism using this memory) which feed their individual decisions. In the course of the simulation different agents accumulate different memories, and thus naturally evolve into a ***heterogeneous*** set of individual decision makers[3].

Repeated cooperation between agents builds up trust which in turn influences the emergence of institutions. It is important to distinguish between ***institution-building proper***, which by itself just constitutes part of the "rules of the game", of the simulation, and its materialization as some ***special form*** of organizational arrangement with some members of this organization enforcing compliance to the rule set[4]. The special form, the realization of an institution, needs to be modeled explicitly by some agents taking over the role of enforcers,

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[3] Heterogeneity is thus not only an exogenous assumption replacing the (mainstream economic) assumption of a set of homogeneous representative agents; it indeed is a *process* which evolves as part of the overall dynamics!
[4] Readers with a background in biology will remark the relation to the concepts of genotype and phenotype – used, of course, in a simulation builder's perspective.

the role of executive power. As empirical observation teaches, executive power is needed for two distinct tasks: (1) It guarantees internal stability (compliance to the organizational rules), and (2) it warrants security from external threats (other organizations trying to invade from outside). The organizational apparatus necessary to exert executive power is always financed by tribute payments of its members to their ruling executive[5].

The mechanism of institution building proposed in the next chapter only represents a small - but essential - subset of the highly complicated processes observed historically. It is just a first approximation to the emergence of institutional authority within a set of agents. With a similar (and consistent) logic the model proposed also takes care of the possibility of the break-up of institutions. In that respect it concentrates on the internal discrepancies, which may lead to the exit of the institutions. The presented baseline model does not cover fights between existing institutions, which might lead to the extinction of one of them[6].

The next chapters show how with an elementary set of essential assumptions the dynamics of the rise and fall of larger political entities on the macro-level, driven by decisions taken by heterogeneous agents on the micro-level can be simulated. This exercise has a threefold goal:

1. It shows the possibility to undertake such a most demanding scientific task, which stretches well beyond several rather established scientific disciplines.
2. It shows the emerging difficulties if one comes to the interpretation of the results of the simulation runs – how to classify them, what can be concluded.
3. It provides a simulation toolset, which can be used to investigate future research questions by simply amending the baseline model.

In achieving these three tasks more new questions arose as answers to older questions were found – which is typical for fruitful research.

2. The Model

Our model is based on Sanchez-Pages and Straub's (2006) analytical model on the emergence of institution. In their model, homogeneous agents are matched randomly to play a game of prisoner's dilemma. As usual, each of the two agents participating in the prisoner's dilemma (PD) has the choice between the two actions of cooperation (C) and defection (D). Since the

[5] When Montesquieu in 1685 analyzed the division of powers within states by comparing the then existing states, this division evidently had already emerged – due to the functional needs of large states' organization.

[6] Note that this is perfectly in line with the evaluation of causes of death in biology: Internal reasons for exit are clearly dominating in real life – and only in the most shallow misunderstanding of Darwin's 'survival of the fittest' death as a mass phenomenon is caused by killing rivals.

game is played simultaneously and communication is prohibited, a priori the two players are not aware of their respective opponent's choice of action. If both players cooperate, they both achieve a payoff of R (reward), if they both choose to defect, they both end up with a payoff of P (punishment). Finally, if one agent cooperates and the other defects, then the cooperator gets a payoff of S (sucker's payoff) and the defector receives T (temptation). Payoffs satisfy $T > R > P > S$ and $2R > T+S$.

In the Sanchez-Pages and Straub-model, in the state of nature, i.e. the absence of an institution, agents achieve the cooperative outcome (C,C) with probability $\alpha \in [0,1]$ and arrive at mutual defection (D,D) with probability $1-\alpha$ [7]. The parameter α represents the level of trust within the society and is exogenously given. However, agents have the option to establish an institution that enforces cooperation between its members. To this end they must choose a leader whom they can delegate the work of enforcing cooperation to. The leader may not participate in the PD game but he may set a fee that all agents willing to join the institution have to pay. Games between members of the institution always reach the cooperative outcome. Games between a member of the institution and an outsider, however, are not under institutional supervision and are treated like games in the state of nature. For convenience, we label the former case (enforced cooperation) as *formal games* and the latter as well as games between two institution-less agents as *informal games*.

With this basic setup, Sanchez-Pages and Straub go on to analyze equilibrium solutions on the number of agents within the institution, optimal fees and threats of secession. While their approach is instructive with respect to a number of issues, it considers only the case of *one* institution versus no institution. Furthermore, their model is static and regards only one time period. In our opinion, a dynamic approach is surely far better suited to catch the subtleties of the emergence and exit of such coalitions between individual agents. Since an analytical model of this dynamic version would hardly be tractable mathematically, we resort to the method of agent based computational modelling (ABM). The model was implemented in Repast 3.1 for Java.

In our model, the world is a two-dimensional grid on which the agents can move around freely. Borders are wrapped around so that the matrix topographically is a torus. If an agent happens to meet other agents within his Von Neumann-neighbourhood he plays a game of PD with each of them. If a cluster of at least three agents exists, these agents may decide to become sedentary, choose a leader and build an institution. Members of institutions are able to leave the institution in each time step, the leader of an institution is allowed to set a new fee

[7] The two asymmetrical outcomes (C,D) and (D,C) are not considered.

in each period. Table 1 in the appendix presents the order of events in the form of a pseudo-code. In what follows, all steps are presented in detail:

Initialization

At the start of a simulation run, n_A agents are distributed randomly across the grid. The random numbers are drawn from a pseudo-random number generator following a uniform distribution. Each agent is endowed with a memory of size m. In this memory the agent stores the opponents' choices of the last m *informal* games. We define informal games as games played between (1) two agents who are not members of an institution, (2) an agent who is member of an institution and an agent who isn't, or (3) two agents who are members of different institutions. In short, informal games are those games which are not supervised by one and the same institution. On the other hand, games played by two agents, who are members of the same institution, i.e. those games where the cooperative outcome is enforced, are labelled *formal games*.

We further define the share of cooperative actions stored in an agent's memory as his personal value for α. If we assume, for instance, each agent to have a memory of the last ten informal encounters, i.e. m=10, then α=0.6 is equivalent to the case that in *any* six out of the last ten informal encounters the agent's opponents cooperated. The size of memory thus represents an assumption on the flexibility of an agent to adjust to new experiences. In this way, we are able to endogenize the evolution of trust α according to those new experiences of an agent. If, for instance, an agent meets a lot of other agents who cooperate, his personal α, i.e. his trust in society, will rise and he will be more likely to cooperate himself in the future. Since we state that only informal games are memorized, we assume that enforced cooperation within an institution doesn't influence an agent's personal level of trust.

Obviously, at the initialization of a simulation run, no games have been played and therefore no actions would be stored in the agents' memories. We assume an exogenously given starting value $\alpha_0 \in [0,1]$, which is equal for all agents and represents a society-wide level of trust at t=0. With this starting value, we construct a random history of encounters for each agent, i.e. a hypothetical history of events that corresponds to the given value of α_0.

In contrast to the perfectly homogeneous agents in the Sanchez-Pages and Straub-model, the agents in our model are heterogeneous with regard to their location within the simulated world and their experiences.

Movement

At the beginning of each time step, the activation order of the agents is shuffled randomly. Then each agent moves randomly to an unoccupied site within his immediate Von Neumann-neighbourhood.

Playing the PD

Leaving institutions aside for a while, the next step lets each agent play a game of PD against each of his Von Neumann-neighbours in random order. In informal games, each agent plays a mixed strategy of cooperating with probability α and defecting with probability 1-α. As stated above, the parameter α evolves endogenously for each agent. This setup is in contrast to the Sanchez-Pages and Straub-model. While the latter only considers cases of mutual cooperation or mutual defection, our model allows for the cases of (D,C) and (C,D) as well.

Building an Institution

A cluster of at least three agents connected through their Von Neumann-neighbourhoods may decide whether to build an institution. An institution guarantees enforced cooperation between its members at the cost of a membership fee. The process of institution formation proceeds in four steps. (1) Each agent within the cluster calculates if it pays to participate in the future institution. (2) Each agent willing to join the institution proposes a fee he would collect from the members of the institution in the case that he would become the leader. (3) The agent proposing the lowest fee is appointed as the leader. (4) Each agent aside from the leader decides whether to effectively participate in the institution under the designated leader and his proposed fee. If after these four steps, a connected set of members and the leader of size > 2 remains, then this connected set becomes an institution.

Step 1: Decision of Participation

At first each of the agents in the cluster calculates if it pays to participate in the future institution by comparing his potential informal payoff in the state of nature with his potential formal payoff as a member of the institution. We assume that agent i estimates his potential profit per period in the absence of an institution according to

$$\pi_i^I = \alpha_t[\alpha_t R + (1-\alpha_t)S] + (1-\alpha_t)[\alpha_t T + (1-\alpha_t)P],$$

where the superscript I stands for informal (institution-less) payoff as compared to formal payoff (within an institution). Obviously, this formula is a rather naïve guess, since it doesn't take into account the probability of not meeting any agents at all and ending up with no playing partners. On the other hand, multiple games per period aren't accounted for, either.

The payoff within an institution is estimated with a similarly naïve guess:

$$\pi_i^F = k_i R(1 - l d_{i,L}) - \varphi.$$

This calculation takes into account the number of neighbours k within the institution who the agent would be guaranteed to cooperate with. Additionally, we assume the quality of enforcement of cooperation to decrease with the agent's distance $d_{i,L}$ to the leader. The distance to the leader is measured as the shortest path between the agent and the leader that traverses only members of the institution, each of who is a Von Neumann-neighbour of the former. The parameter $l \in [0,1]$ is exogenously given and serves as a weight for the loss in quality of enforcement. Finally the fee φ for participating in the institution is deducted. Since the institution hasn't come into existence yet, distance to the leader can't be determined. For the sake of simplicity we assume that each agent believes he will become the leader, so that $d_{i,L}=0$ during this step of institution formation. The fee φ is given by $\varphi=c/(s-1)$, where c denotes the cost accruing to the leader from enforcing cooperation and s is the size of the institution, i.e. the number of members including the leader. We assume that the leader himself needn't pay the fee. Since at this moment it is not clear to the agents how large the institution will be in fact (see below), they use as an estimate the size of the cluster they are part of. Finally, the cost of enforcing cooperation is given by

$$c(\bar{d}, s) = \bar{d}\sqrt{s},$$

where $\bar{d}$ represents the average distance of the leader to all members of the institution. Obviously, the chosen cost function is just one of many possible alternatives, but it serves as a first reasonable and parsimonious approach. Future research may well investigate the effects of different cost functions.

Once again, since the leader is not known at the moment, each agent assumes that he himself will become the leader of the institution in order to calculate the average distance to the other agents. Each agent in the cluster now evaluates the benefits of participating in the institution and compares his informal payoff π_i^I with his formal payoff π_i^F. Only if the latter exceeds or equals the former, the agent is willing to participate in the institution.

Step 2: Proposing a Fee

In the next step, each agent willing to participate in the institution proposes a fee. We assume that an agent estimates his fee proposal such that the sum of collected fees would equal the cost of being the leader, i.e. we assume that leaders don't factor in a profit margin or formally

$$(s - 1)\varphi = c(\bar{d}, s).$$

Please note that in contrast to Sanchez-Pages and Straub, in our model leaders are allowed to play the PD game. This choice was guided only by the comparable ease of implementation.

Step 3: Appointing a leader

Next, the agent proposing the lowest fee is appointed as the leader. If more than one leader proposes the lowest fee, one of them is appointed randomly.

Step 4: Final Evaluation

Finally, each agent aside from the leader compares his informal payoff with his formal payoff given the designated leader and his proposed fee. If the formal payoff equals or exceeds the informal payoff, the agent joins the institution effectively.

Only if after this final evaluation a connected set of at least three agents (including the leader) remains, an institution emerges. All agents participating in an institution become sedentary and remain so until they eventually leave the institution or the latter breaks apart.

Joining an Already Existing Institution

As shown in the pseudo code in Table 1 in the appendix, if an agent is located in the Von Neumann-neighbourhood of a member of an institution, the former may choose to join the institution as well. Again, this agent compares his informal payoff with his hypothetical payoff from joining the institution. If the formal payoff is larger or equal than the informal payoff, the agent joins the institution.

Leaving an Institution (Re-evaluating Membership)

In each time step, every member of an institution re-evaluates his gains from participating in the institution. If due to changed circumstances (e.g. changed neighbourhood), his formal payoff no longer exceeds or at least equals his informal payoff, the agent chooses to leave the institution. All members not connected anymore to the leader are forced to leave the institution as well. If the size of an institution falls beneath 3, it ceases to exist.

Re-evaluating the Fee

In every period, each leader of an institution re-evaluates the fee he collects from the members of the institution. If the sum of fees collected in the previous period is smaller than the cost accrued to him for enforcing cooperation, the leader suffers a loss. In this case, he raises the fee such that the collected fees would equal the cost in the current period.

3. Visualization of the Model

Agent-based models offer the huge advantage that they are capable of visualizing the dynamics of its formal core, which may help the researcher to get a deeper understanding of the model dynamics. In economics, visualization of complex processes is usually limited to time-structured graphs. In agent-based models, the scientist can explore model dynamics with snapshots of specific runs. While some may consider this to be just an aesthetic issue, in fact, it possesses powerful didactic potential. In our case the visualization plays a major role, even more, it's the central element to get a look behind the curtain of the vast dependencies between model parameters, dynamic behaviour and outcome. In Appendix 2, we present the visual interface of our simulation in detail and provide a description of the most important components.

We would like to conclude this section by presenting a number of typical agent patterns in order to invigorate the formal description of the model.

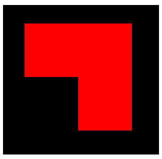


Figure 1a

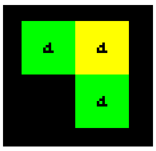


Figure 1b

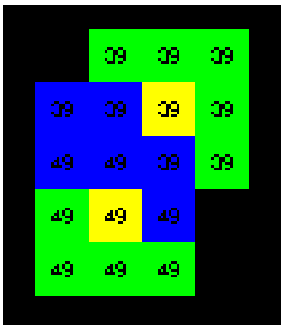


Figure 1c

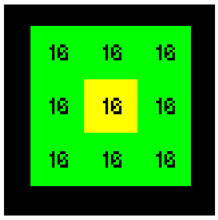


Figure 1d

As already mentioned above, an institution can only emerge if there are at least three neighbouring agents. Figure 1a presents such an agglomeration of agents which we termed a *cluster*. Figure 1b illustrates an institution with three agents. The members of the institution are coloured green, the leader is coloured yellow. In this way we can keep track of the leader's position within a specific institution. The numbers within each agent represent the id-number of the respective institution. This additional visual information helps us to keep track of specific institutions. In this particular example, the number 4 illustrates the fourth institution having come into existence during the current simulation run. Figure 1c shows two neighbouring institutions. To highlight members of an institution neighboring another institution, we colour them blue. Finally, Figure 1d shows a typical example for an institution in a setting with influence weight parameter l=0.2. Different values for l tend to produce different institutional arrangements.

With these basic mechanisms we are able to sketch the dynamics of emergence and exit of institutions endogenously. The following section deals with sensitivity analyses of a number of parameters which we identified as crucial instruments.

4. Sensitivity Analyses of Instruments

Preliminary testing of the simulation soon revealed four parameters which influence the behaviour of the model to a large degree and which we therefore choose as instruments for conducting our further analysis. In order to gain a deeper and more systematic understanding of these four instruments, we performed extensive sensitivity analyses for each of them holding all other parameters constant. The four instruments are the initial trust level α_0, the total number of agents n_A, the memory size m of an agent and finally the distance weight parameter l.

Initial Trust Level α_0

We first explore the baseline case of an institution-free world. In our model, this is achieved by simply setting the distance weight parameter to 1. In this case, the formal payoff π_i^F is always negative, thereby guaranteeing the impossibility of emergence of institutions. The first question posed is how the initial trust level α_0 influences the endogenous evolution of trust. To provide an answer to this question we measured the average of all agents' trust levels at t=5000 given a specific value for α_0. This average trust level of all agents can be regarded as a simple measure for the trust level of the society at a given moment. This exercise was repeated 50 times for each specific value of α_0 using a different random seed for each run. Then we calculated the average value of the societal trust levels of these 50 runs to minimize the influence of random fluctuations on the results.

Plotting the initial trust level α_0 on the x-axis and the average societal trust on the y-axis reveals a nearly perfectly linear fit between the two values (see Figure 2 for an example). Obviously, for α_0=0 the model stays at α=0 forever, since all agents play defection with probability 1-α=1 in every game and no other choice is ever memorized. Analogously, for α_0=1 the model is stuck at α=1.

Note that the linear relation between α_0 and α_{5000} is not due to the relative constancy of α. On the contrary, the overwhelming number of runs converges to either perfect defection (α=0) or perfect cooperation (α=1) after a prolonged period of oscillations. It is only the average over all runs that reveals this linear relationship.

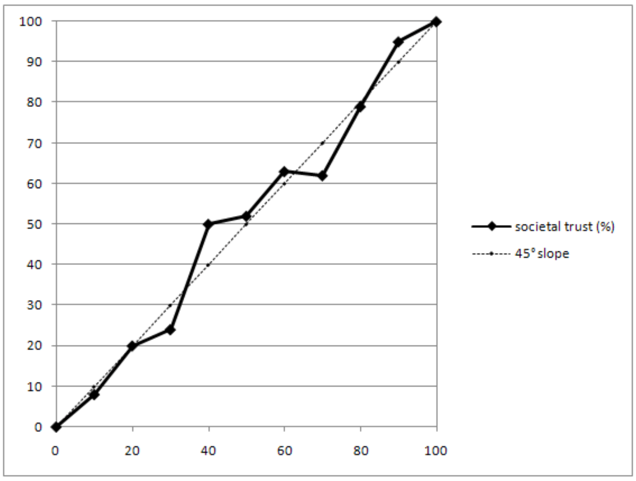


Figure 2: Societal trust level at t=5000 in dependence of α_0

(in %, averaged over 50 runs with different random seeds)

Instruments set to: n_A = 90, l=1.0, m=10, grid size=30x30

Number of Agents n_A

At first we expected the population density, i.e. n_A/(grid-x-size*grid-y-size) to have an effect on model behaviour. But our expectations were disconfirmed by extensive testing of the simulation. The absolute number of agents n_A itself, however, is responsible for changes in the behaviour of the model. Still considering only the baseline case of an institution-less world, an increase in the number of agents n_A seems to improve the linear fit presented in the subsection above, although the results are not conclusive. A much more surprising effect of n_A makes its appearance only in combination with certain values of the distance weight parameter and is therefore presented in the analysis of the respective instrument below.

Memory Size m

Changes in the memory size m seem to wield no influence on the linear fit between α_0 and α_{5000}. To understand the effect of changes in m we therefore have to take the analysis to a less aggregated level and investigate the evolution of α in individual simulation runs. We expected that the memory size would directly affect the fluctuations of the societal trust level by dampening oscillations. In order to substantiate our conjectures, we conducted a number of simulation runs with α_0=0.5 and a broad range of different values for m. We measured the time of convergence of α for each value of m. This analysis was conducted for different values of the torus size (10x10, 20x20 and 30x30) with a constant population density of 25%. For each single run, the same random seed was used to isolate only the effects of the memory size. Figure 3 illustrates the results of various runs conducted on a comparably small 10x10 grid with 25 agents. It shows that increased memory size definitely smoothes the time series of societal trust. Time series with a smaller memory fluctuate in a more pronounced manner than the ones with a larger memory. For very high values of m (Figure 3, m=100), convergence is beyond the time horizon of the experiment.

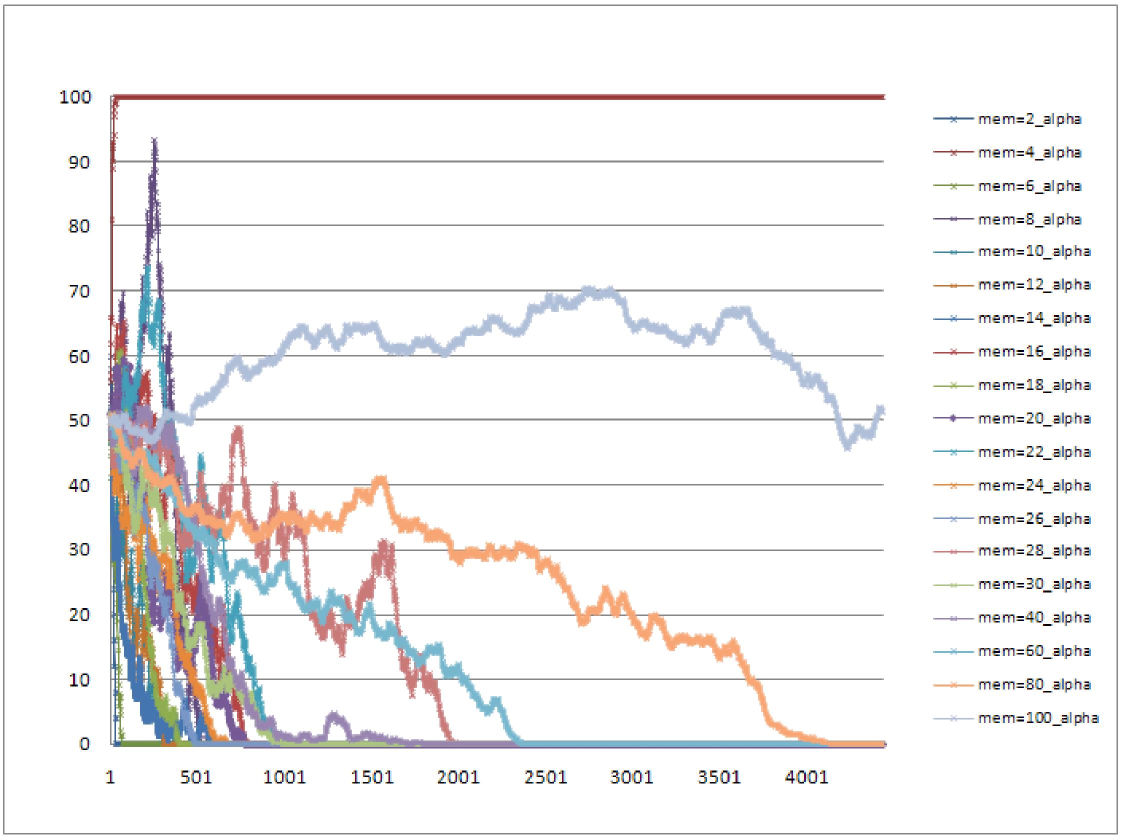


Figure 3: Evolution of societal trust in a 10x10 grid with 25 agents and α_0 = 0.5

Figure 4 shows a scatter plot of the point of time of convergence and the memory size illustrating a good linear fit between these two variables.

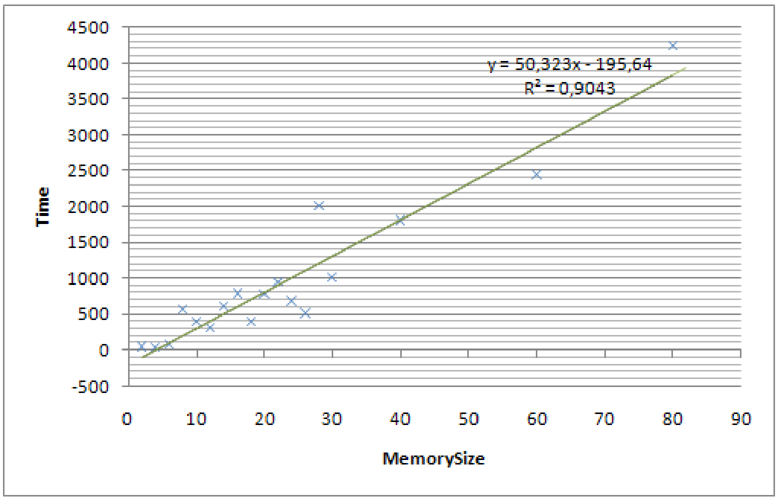


Figure 4: Scatter plot of convergence-time and memory size in a 10x10 grid with 25 agents and $\alpha_{start} = 50$

In order to confirm this result we performed further experiments with varying grid sizes and different random seeds. Details for various settings can be found in Appendix 3.

In general, the linear relationship between convergence time and memory size holds for a great variety of different parameter settings. A higher memory leads to slower convergence and to smoother time series of the societal trust α. Consider a memory of 100 turns and think about its consequences, there will always be a kind of small probability that an agent will decide different. This small probability may vanish over time, but events from the past usually stay resident in the future, as Sigmund Freud would confirm too. An agent's capacity to store actions from the past over a long period, by the means of a complex cognitive apparatus as e.g. the human mind, makes her very indecisive, but also quite resistant to spontaneous surprising shocks.

Influence weight l

We explored the effects of the influence weight parameter *l* for the values 1, 0.5, 0.25 and 0, respectively. The case of *l*=1.0, i.e. the institution-less case, has already been considered above. Intuitively, decreasing *l* should increase the occurrence of institutions. But first, we will take a look of the effects of this parameter on the societal level of trust, again measured at t=5000 and averaged over 50 runs. Figure 5 depicts the (α_0, α_{5000})-diagrams introduced above for several values of *l*.

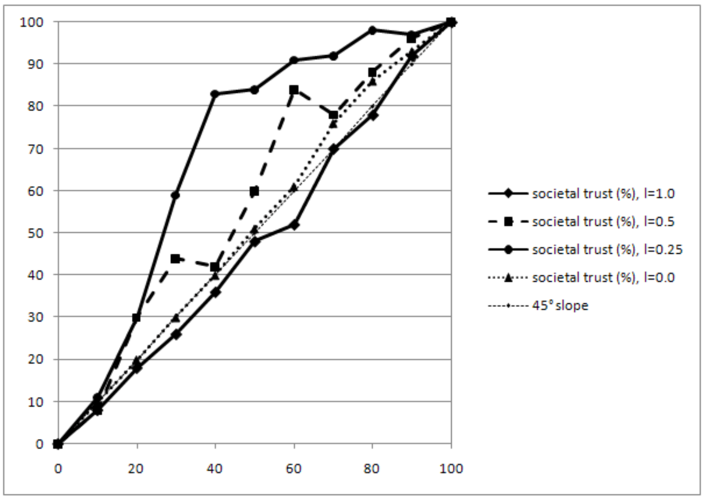


Figure 5: Societal trust level at t=5000 in dependence of α_0
(in %, averaged over 50 runs with different random seeds)
Instruments set to: n_A = 40, m=10, grid size=10x10

The case of *l*=0 reveals a similar outcome as in the case of *l*=1. Again a linear relationship between α_0 and α_{5000} can be observed, this time, however, for different reasons. Setting *l* to 0 implies no loss of utility with increasing distance to the leader of an institution. Therefore, comparably expansive institutional arrangements emerge very soon in the simulation runs until all agents are members of stable institutions. At this point, no further informal games take place, thereby freezing α at a value close to the initial α_0. The cases between these two extremes appear more interesting. For *l*=0.5 the linear fit no longer applies. Instead, the societal trust level lies strictly above the initial level of trust. For *l*=0.25 this effect is even more pronounced. Agents tend to build institutions when trust is comparably low. The possibility of building institutions, however, seems to raise the overall level of trust within a society. This result is more nuanced than – some might even say in contrast to – the existing literature which often assumes a simple negative relationship between trust and institutions[8].
Given *l*=0.25, if we now increase the number of agents n_A, the effect is much more pronounced. Figure 6 shows the outcomes for several values of n_A.

[8] For a careful analysis of trust and institutions compare Noteboom (2007)

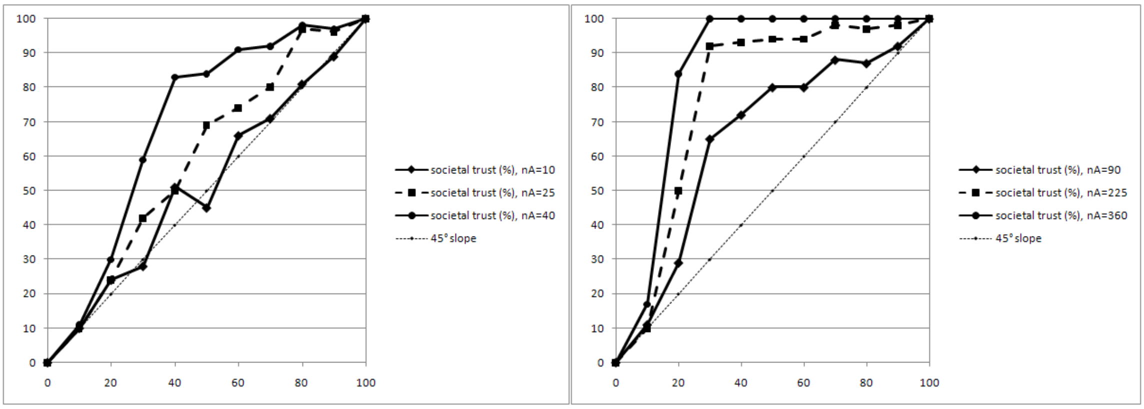


Figure 6: Societal trust level at t=5000 in dependence of α_0

(in %, averaged over 50 runs with different random seeds)

Instruments set to: l=0.25, m=10, grid size=10x10 (left panel), grid size=30x30 (right panel)

The values n_A=10, 25 and 40 were investigated on a 10x10-grid, the values n_A=90, 225 and 360 were explored on a 30x30-grid. Please note that these values correspond to a population density of 10, 25 and 40 percent, respectively. These results also disconfirm our original expectation that population density matters. Instead, it is the absolute number of agents which seems to matter a lot. It is not until there is a critical mass of agents that the benefit of institutions comes into play in the form of increased societal trust.

5. Formalised Storytelling

Now we are able to present some scenarios which include crucial economic stories for further analysis. In general our agent-based model is capable of producing complex processes with emergent patterns as we can observe them in political economy. Even if specific parameter settings and implicit assumptions in the formal apparatus are kind of *ad hoc*, the value added lies in emerging aggregate patterns which can be identified in sample runs of the simulation. These patterns have significant similarities to a huge set of observable complex adaptive systems, as e.g. the political economy. There we often deal with contradictive socioeconomic forces which produce unpredictable outcomes, but also have *ex post* regularities.

For that reason we want to present 4 different scenarios of system dynamics, our model can reproduce. The first case deals with a rather fast building-up of institutional blocks which stabilize or freezes over time. It is a static system state. In that case societal trust converges very fast to a specific constant level – agents don't move anymore because they are all settled in institutions. The second case is completely the opposite. There is no incentive to join institutions or to stay in institutions for a longer period. There we can find short pulses of institution-building, but they won't be stable over time and the system converges to total trust. It is also a static system state.

Then the third case reveals a little bit more peculiar features and thus more space for good stories; it deals with 2 phases in the dynamics of the system and includes a transition from scenario 1 to 2. Here ***institutions build up very fast*** and are stable, ***but at a crucial point in time***, one can observe a ***fast breakdown of all of them*** and societal trust converges to cooperation. But the fourth case is the most curious one, the system dynamics stay in an oscillating phase. This scenario includes some kind of boom-bust cycles of institutional regimes over a long time horizon. Here we almost don't find convergence to any static system state, or perhaps only in far away future periods.

In all cases the influence weight parameter plays the most crucial and sensitive role, it is a kind of structure parameter which can lead to very different outcomes through subtle adjusting. The adjustment of the influential radius of the leader can trigger phase transitions in our model.

Scenario 1 – Static Institutional Freeze – A Defective World

Scenario 1 implies a world full of static institutions with settled agents, all in fear of the defective battlegrounds in the "natural world", as Figure 7a shows. The evolution of societal trust just plays a major role in the beginning of the scenario, where the agents start in the natural state. We analysed this scenario with a 30% start value of trust; that means agents have a 30% propensity to cooperate. By that agents flee very fast in institutional settlements, because the world outside is kind of tough and hence institutions play the role of refugee camps in a quite early moment of the game. Institutions build up either slowly or fast dependent on the level of leader influence i. We tested several levels of influence (l=0.1, 0.15, 0.2, and 0.25, respectively) on a 30x30 grid with 250 agents. Agents are equipped with a memory size of 10 encounters per agent, which represents a rather short-term memory.

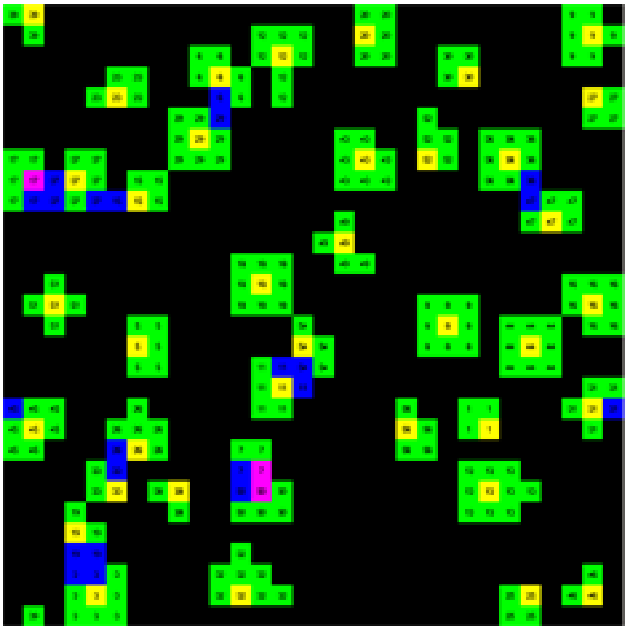


Figure 7a : Screenshot of static state with *l*=0.2 in a 30x30 grid with 250 agents α_0=0.3, m=10

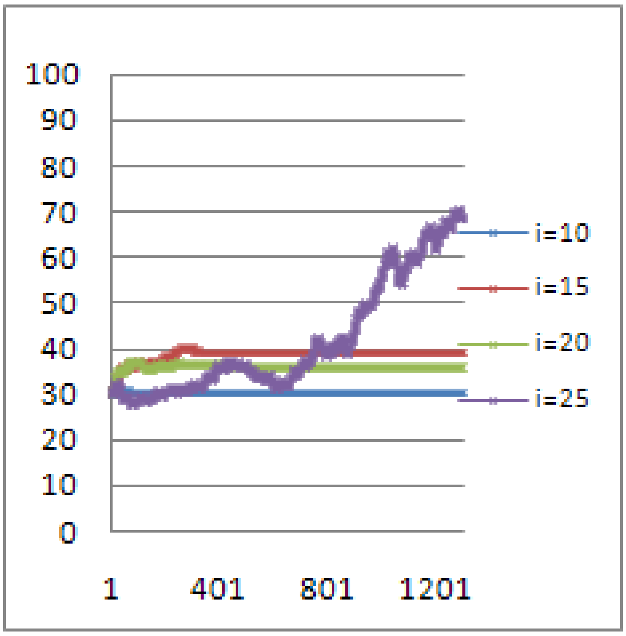


Figure 7b : Evolution of societal trust dependent on influence in a 30x30 grid with 250 agents, α_0=0.3, m=10

As you can see in Figure 7a, agents build up rather big institutions. In that case the scenario froze after about 350 turns, which is very fast. Of course agents at the border lines of neighbouring institutions can still play PD, therefore societal trust may change slightly, but will converge by time to about 38 % of cooperation. Now we can almost summarise that a low societal trust level leads to more and more institutions. That's because agents feel safe in the setting and have no incentive to leave their institutions. Another fascinating thing here (but also observable in other scenarios) is that agents build up institutions with the same timing independent from the influence level, which you can see in Figure 7c. In all cases stability rises with the same rate[9]. The one and only difference in the first phase of the scenario of different influence values can be viewed in Figure 7d. Here you can see the evolution of the number of formal agents; agents who are a member of an institution. The curves rise at different speed, dependent on the influence level again. The fastest one is the blue curve (*l*=0.1), which completely follows the logic of the model. With such a low level of leader influence agents can jump on institutions very fast; or by explaining it with causality the other way around: leaders can hold members very easily.

[9] Note that all curves, except *l*=0.25, in Figure 7c would increase infinitely, because stability won't break down anymore. They are just cut off at different levels, after their convergence points.

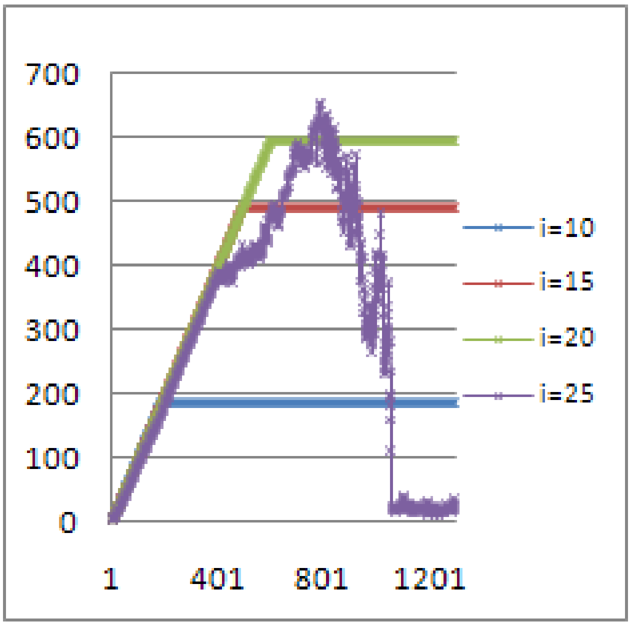


Figure 7c : Evolution of average age of institutions dependent on influence in a 30x30 grid with 250 agents α_0=0.3, m=10

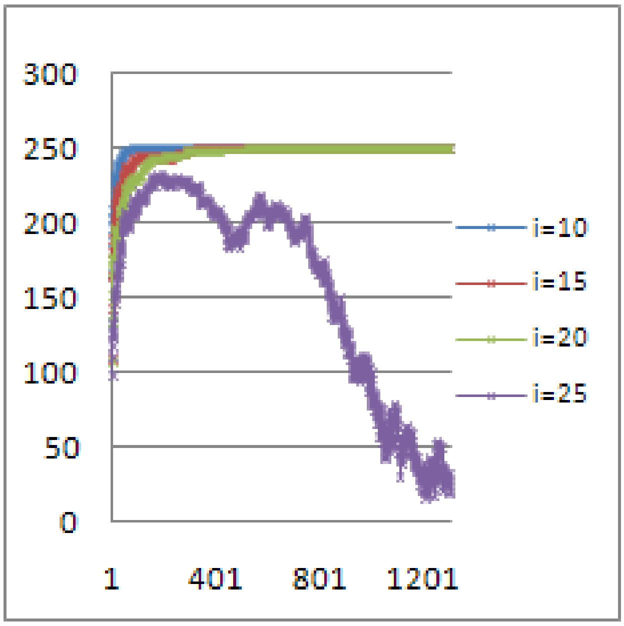


Figure 7d : evolution of formal agents dependent on influence in a 30x30 grid with 250 agents α_0=0.3, m=10

Compared to Figure 7b, it is the same curve which converges fastest at a constant level of societal trust. Hence the higher the influence the more difficult it is to hold more and more agents for the leaders. Going to a level of *l*=0.25, the scenario swaps suddenly. The influence level is too high for the "system" to get into a frozen institutional steady state. You can see in Figure 7c that the stability variable holds constantly till 400 rounds, then the first institutions break down a wave of somehow creative destruction. Agents seem to check that the natural world is not that bad if all of them would start to cooperate, but that's already the transition to scenario 2 and to the next story.

Scenario 2 – Static State without Institutions – A Cooperative World

In scenario 2 we face a rather odd situation, most mainstream economists would say. Nevertheless there are some other economists who would say the opposite, as e.g. Putnam (1993), Zak and Knack (2001). Putnam shows in his huge institutional analysis of Italy that the rather poor South is more equipped with bonding social capital than bridging social capital. If we assume that bonding social capital – affinity to keep links with friends and family – means more to trust and that bridging social capital means more to reputation – affinity to link with people in business and that like – then we can follow for our scenario 2 that this is a world quite similar to the South of Italy, where people keep their family links and avoid to stick to institutions.

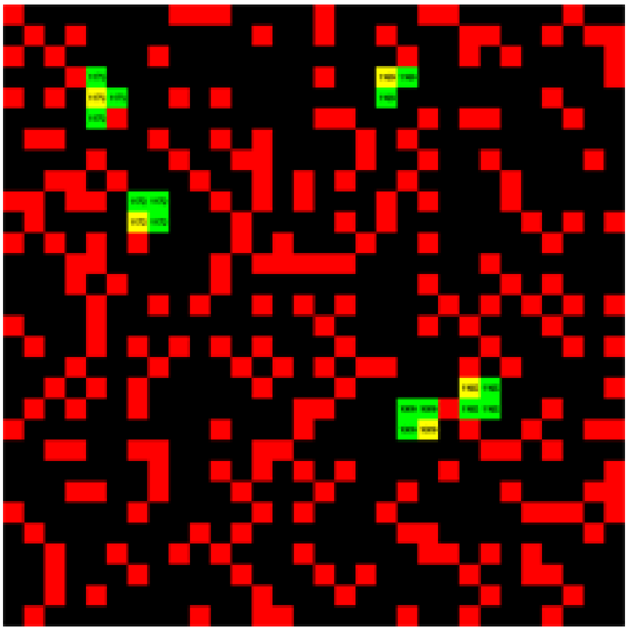


Figure 8a : Screenshot of static state with influence *l*=0.3 in a 30x30 grid with 250 agents α_0=0.5, m=10

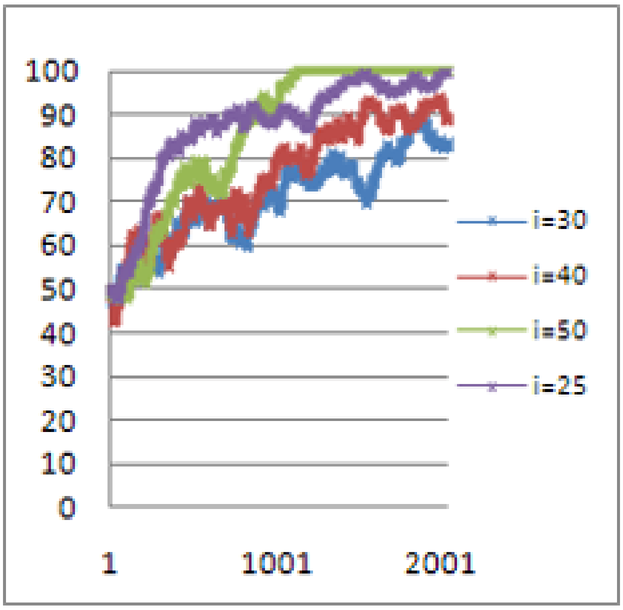
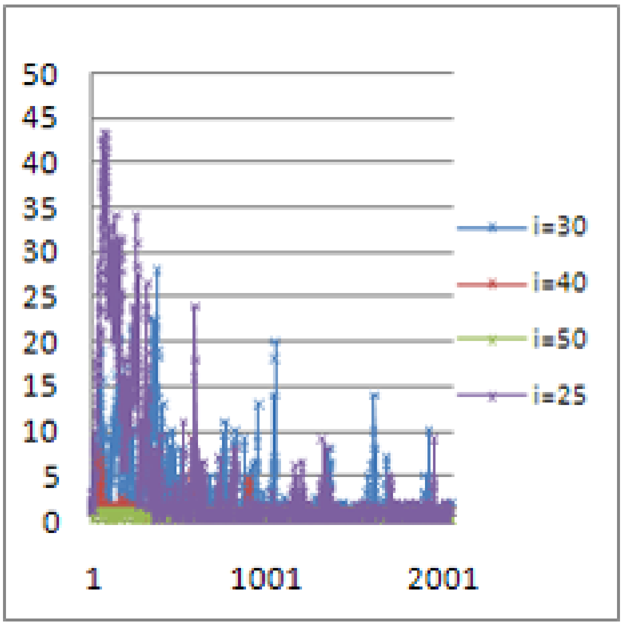


Figure 8b : Evolution of societal trust dependent on influence in a 30x30 grid with 250 agents α_0=0.5, m=10

That's why our endogenised societal trust is more comparable with bonding social capital then with bridging social capital in a first instance. Nevertheless scenario 2 also contains emergence and exit of institutions, but here they vanish more frequently as you can see in Figure 8c, which shows the evolution of the average age of institutions; they don't live very long. As we mentioned in scenario 1, we face a transition in the case of *l*=0.25. The *l*=0.25 curves in all 3 figures (7b-d) show the most stable institutions, at least at the first phase of the scenario. Whereas the other influence settings only show up with short pulses of institution-building, which can also be identified in the evolution of formal agents (Figure 8d).

In this scenario we can identify a strong tendency towards cooperation. As you can see in Figure 8b, almost all curves converge to 100% cooperation very fast, hence agents don't need the institutional settlement anymore. Further we also have to consider that institutions indeed come up frequently, but they just keep stable for a short time and that kind of sequence keeps very long till societal trust converges to complete cooperation.



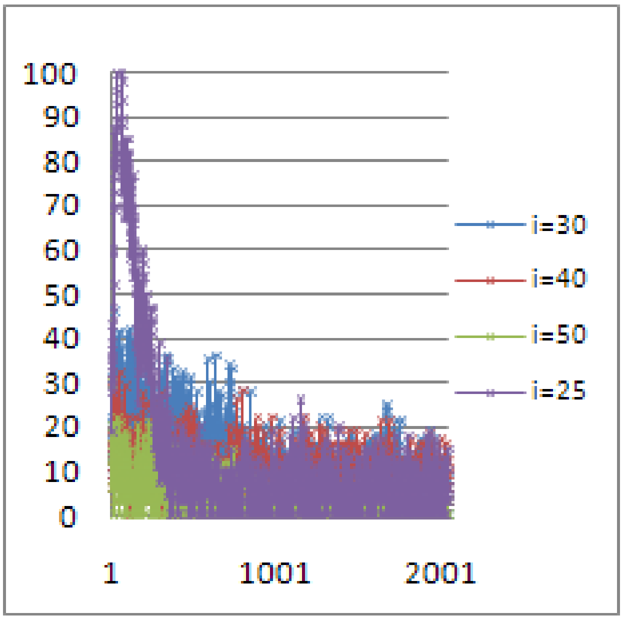


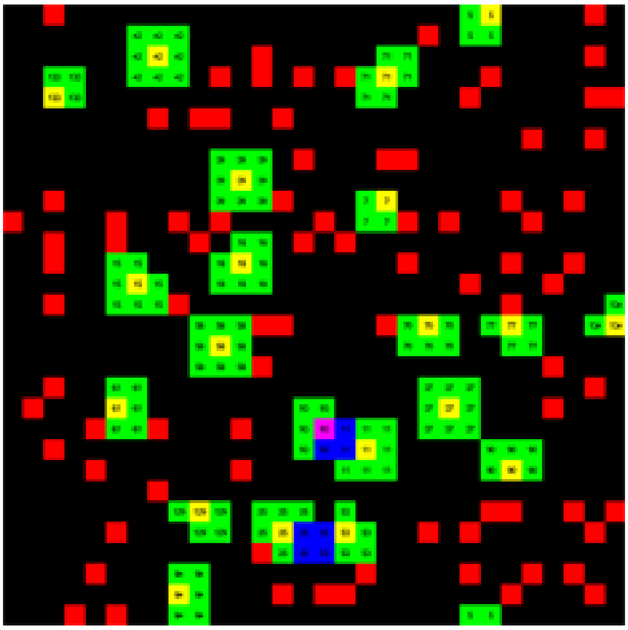
Figure 8c : Evolution of average age of institutions dependent on influence in a 30x30 grid with 250 agents α_0=0.5, m=10

Figure 8d : Evolution of formal agents dependent on influence in a 30x30 grid with 250 agents α_0=0.5, m=10

In that sense, scenario 2 leaves us aside with a kind of static institution-less state in a world full of cooperation.

Scenario 3 – Institutions as Learning Vehicles

In scenario 3 we face a very interesting situation. Institutions build up very fast and are stable for a very long time. Still in believe that the system will converge to scenario 1 – the "freeze" case – agents suddenly make a phase transition to scenario 2 – the cooperative world. We tested this scenario again on a 30x30 grid with 225 agents (25 % population density), but this time with the crucial influence level of 25%, to see how the system may swap to different scenarios. We made case studies for different start values of societal trust, as you can see in Figure 9b-c. Starting with 20% of cooperation in societal trust still leads to scenario 1 and institutions dominate the world, then with a start value of 30% the system already swaps. First we called this experiment *peak experiment*, because the simulation produced lots of peaks in the average age of institutions in the first phase of the scenario, as Figure 9b shows. Consider the case with a start value of 30%. You can see that institutions are stable over 450 periods and no one would think that this might change, but we identified that societal trust moves up to more cooperation during this phase and finally "persuades" a critical mass of agents to exit institutions, entering the "natural" state again.



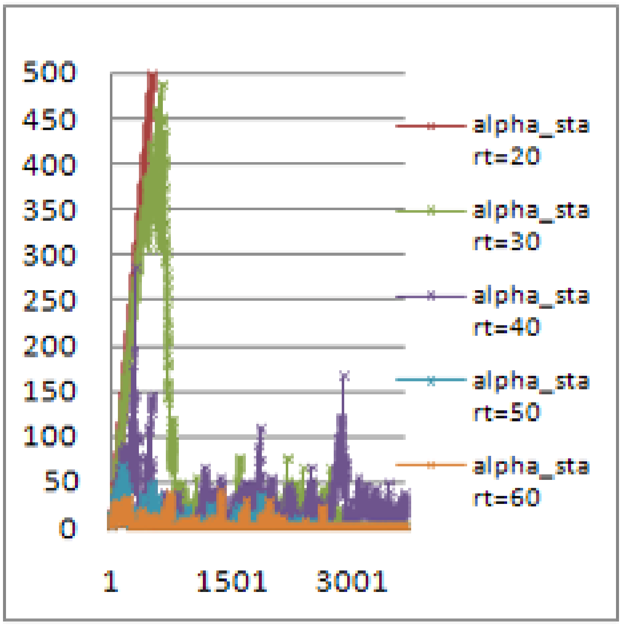
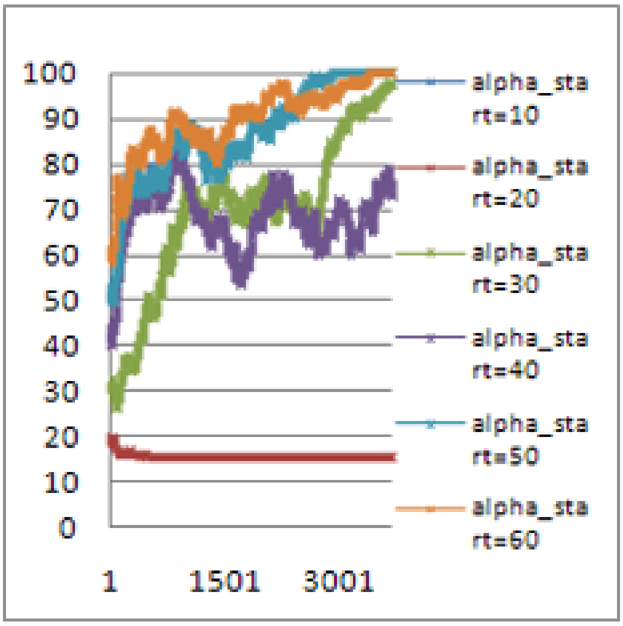


Figure 9a : Screenshot of a Stability-Peak in a 30x30 grid with 225 agents l=0.25, m=10, α_0=0.3

Figure 9b : Evolution of average age of institutions dependent on start value of trust in a 30x30 grid with 225 agents l=0.25, m=10

This was really surprising; hence we tried out different start values for societal trust, as the figures show.



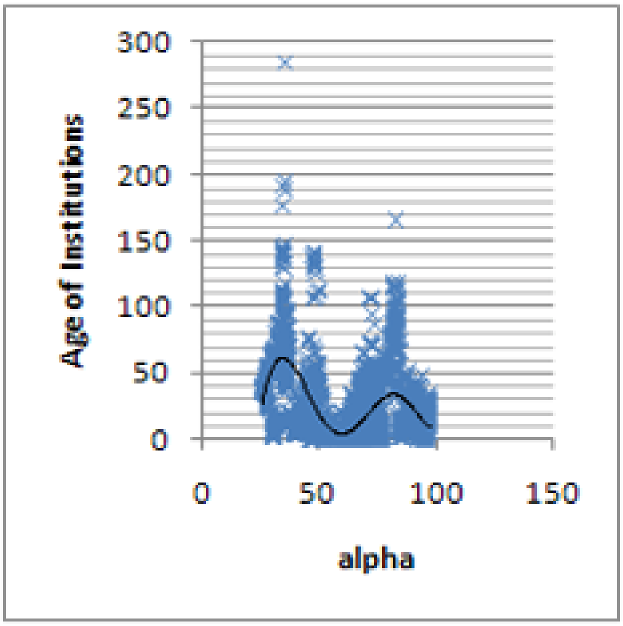


Figure 9c : Evolution of societal trust dependent on start value of trust in a 30x30 grid with 225 agents l=0.25, m=10

Figure 11d : scatter plot age of institutions vs. societal trust in a 30x30 grid with 225 agents l=0.25, m=10, α_0=0.3

We had no handy solution ready for this, so we decided to do a little bit more deeper analysis and plotted the age of institutions vs. societal trust (Figure 9d). What can you see there?

The scatter plot shows correlation of the two variables in a quite unusual manner. One can see the first stability peaks in the phase of low alpha. With a rising alpha the peaks get smaller and finally vanish. We can assume at least two stability upswings and following downswings in a boom-bust manner. Now, we interpreted this as learning of cooperation. Institutions play the part of the teacher. The emergent structure of an institution shows the agents how cooperation works, then societal trust rises, cause informal agents have good encounters with formal agents, even when they don't join the institution; it's getting into their memory. Then in phase 2 of the scenario there has to be a critical mass of cooperative agents to break out of the institutions. If after this phase, trust is not high enough then agents resume building up institutions and the game starts again like a boom-bust cycle. Indeed this scenario always ends up in scenario 2, but the intermediate dynamics are quite unusual.

We can explain the cycle of a world full of institutions to a world without institutions via an institutional learning mechanism for cooperation. This seems quite comprehensible, but needs lot of more future research to prove.

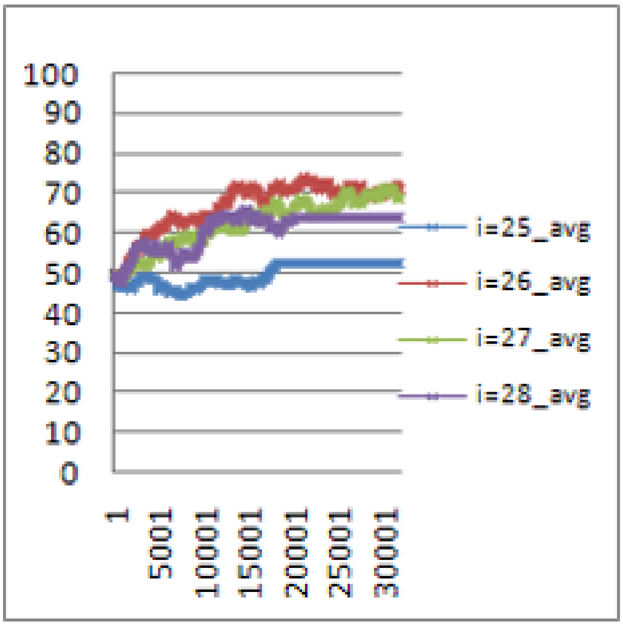


Figure 10a : Evolution of societal trust dependent on influence in a 30x30 grid with 250 agents m=100, α_0=0.5

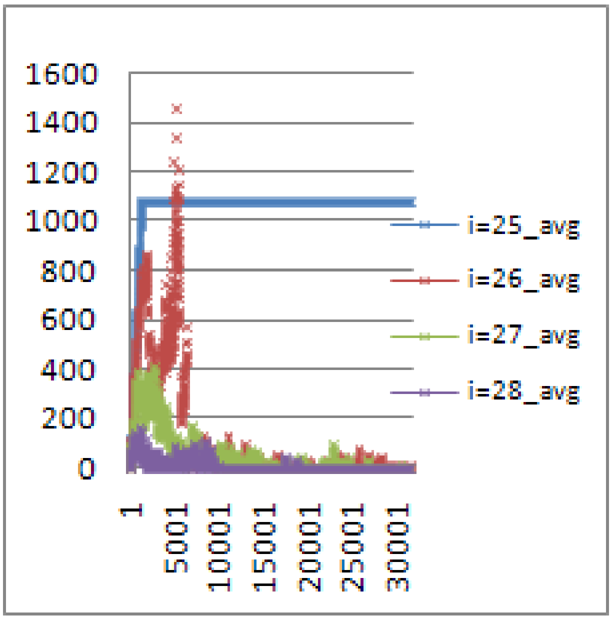


Figure 10b : Evolution of age of institutions dependent on influence in a 30x30 grid with 250 agents m=100, α_0=0.5

Scenario 4 – Boom and Bust of Institutional Regimes

Scenario 4 offers a long-term observation of the model. We tested a setting with ultra-high memory size of 100 encounters on a 30x30 grid with again 250 agents. Our control variable was again the influence weight parameter. Generally the scenario is similar to scenario 3, except that the boom-bust cycles hardly converge to a steady state. Institutional regimes come and go in this scenario; emergence and exit shake hands in a kind of chaotic regularity – a complex adaptive world. Hence, we can proudly propose that we built a model which is capable of oscillating very, very long (about 30.000 periods as you see in Figure 10b). The last 4 figures (10a-d) show the evolution of societal trust, the number of formal agents, the stability of institutions via their average age and the evolution of the number of institutions. As you see we are confronted again with about 3 phases in the scenario. At first institutions build up very quickly and are very stable, but then agents have learned again to cooperate and break out. These dynamics repeat till period 30.000 in nearly every case, nevertheless the curves are smoothing slowly down to a practicable stable level of the amount of institutions and a practicable stability state.

Additionally we have to point out, that the spreadsheet software was not able to manage this huge amount of data, therefore we used the moving average within an interval of 10 periods for this dataset.

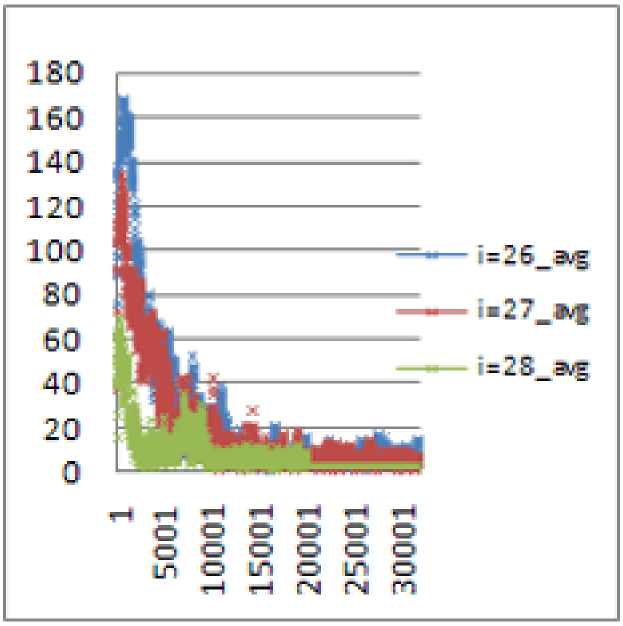


Figure 10c : Evolution of number of formal agents dependent on influence in a 30x30 grid with 250 agents m=100, α_0=0.5

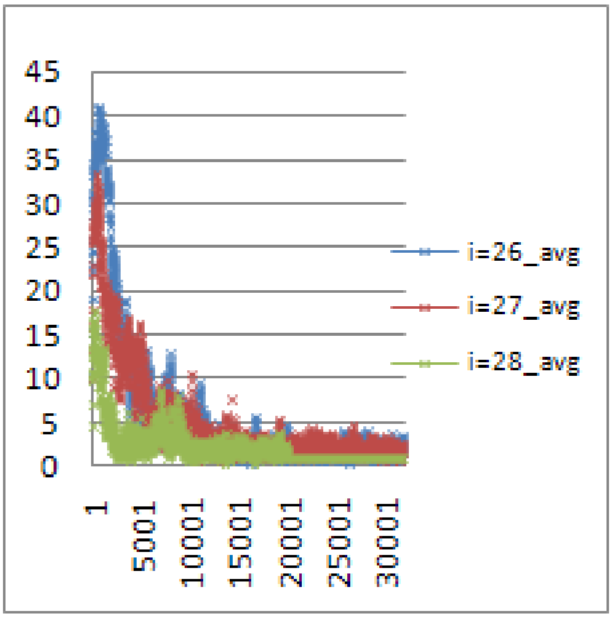


Figure 10d : evolution of number of institutions dependent on influence in a 30x30 grid with 250 agents m=100, α_0=0.5

Conclusion

The framework presented and the simulations carried out clearly encourage further research in the envisaged direction. Of course, most of the issues explicitly studied so far are just one example of what could be seen as essential features of emergence and exit of institutions in human societies. Critics may point at the absence of the concepts of power and exploitation in the framework we use. In the specific simulation study we chose this is indeed the case as far as we do suggest the ***logical*** primacy of voluntarily made decisions of agents as essential reason for the emergence of institutions. Even in such an environment, where coercive power relations between agents are absent – possibly centralized and monopolized by an exogenously given ruling political entity – it is possible to observe a wide variety of forms of emergence and exit of institutions. But note that we had to include elements that point at the transition of our example to models of power and exploitation: The rules for the fee paid to the agent leading an institution as well as the rule for choosing this leader are just typical short-cuts in the spirit of competitive market relationships to keep dynamics simple. Extending our approach by replacing them with ideas reflecting pre-existing power relations securing exploitation would certainly enable our example to be a more adequate image of the historical emergence of institutions – where there has been a ***historical*** primacy of coercive power and exploitation compared to voluntary interactions on markets. Implicitly we thus assume that historical primacy can be better understood by a reversed logical primacy, i.e. that the study of the properties of the well developed system (where some historically earlier features are even neglected) provides the possibility to better understand its historical emergence.

Extensions of this kind clearly hint at opening up new dimensions of heterogeneity of agents. While the dimension of heterogeneity along the trust parameter of a PD game is important, it is tempting to challenge the homogeneity of this PD game. Not only can the pay-off matrix be used to structure the population by allowing for mixed strategies, e.g. John Maynard-Smith's famous hawk-dove examples in biology[10]. There also is the straight-forward possibility to introduce a third action, aggressive coercive force, in the internal models of some agents to supplement the more passive defunct action. With these 'warrior agents' exerting coercive force within the institution as well as to the outside world a more

[10] Compare Maynard-Smith (1982).

sophisticated rule for choosing a leader becomes mandatory[11]. And the rules for accession to and exit from an institution for primitive 'servant agents' will then have to change too. In the sequel the emergence of social norms, of more soft variants of informational power, could be introduced[12]. Finally split-up and heterogeneity of institutions would necessarily be an important topic. In the face of the difficulties of existing global (e.g. financial) institutions some path-breaking new theories are currently emerging[13], and are waiting for formalized story telling of the kind we are proposing.

It is needless to say that all these attractive extensions go beyond the scope of this paper. This paper has shown that even with a limited – but well specified – range of heterogeneity of agents, interesting and important features of the dynamics of the system can be found. Indeed the variety of possibilities we encountered surmounted our ability to find oversimplified general results – we just had to restrict ourselves to some modest suggestions. Reframed as a positive statement this means that additional specification along the lines sketched in the previous paragraph is urgently needed. A task to be accomplished by future research.

[11] Note how close such a description immediately would be to Georges Duby's historical studies on the Middle Ages (Duby 1973).
[12] An excellent example of how game theory models can be used to do so is Bicchieri (2006).
[13] An interesting example is Vibert (2007).

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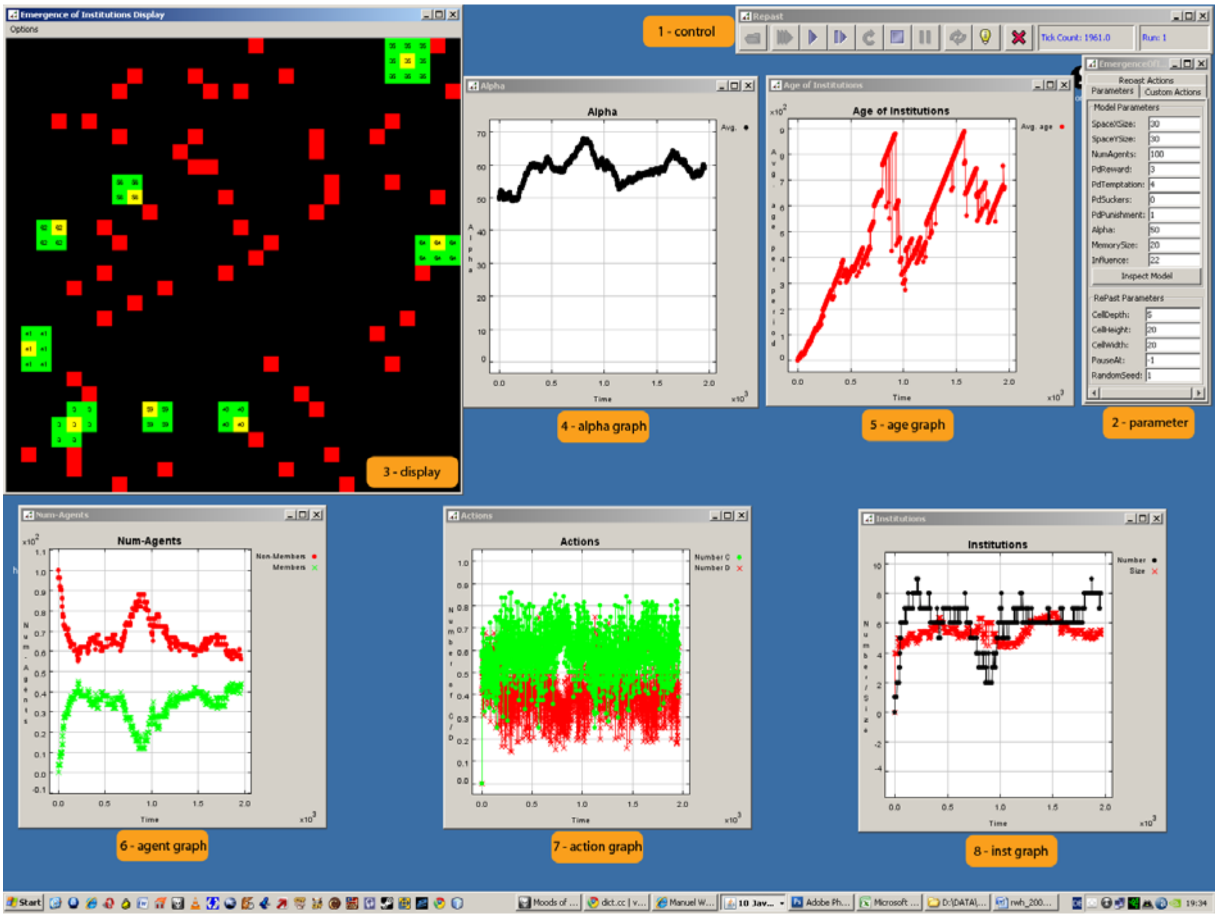
Appendix 1 – Pseudo Code

```
Initialize model
DO t times
    Shuffle activation order of agents
    FOR EACH agent DO
        Move
    END FOR EACH
    FOR EACH leader of an institution DO
        Re-evaluate fee
    END FOR EACH
    FOR EACH member of an institution DO
        Re-evaluate membership in institution
    END FOR EACH
    FOR EACH agent without institution DO
        IF member of institution within Von Neumann-Neighborhood
THEN
            Decide whether to join institution
        END IF
    END FOR EACH
    FOR EACH cluster > 2 agents with institutions DO
        Decide whether to build an institution
    END FOR EACH
    FOR EACH agent DO
        Play against all Von Neumann-neighbors in random order
    END FOR EACH
    FOR EACH member of an institution DO
        Pay fee to the leader of the institution
    END FOR EACH
    FOR EACH leader of an institution DO
        Pay the cost of policing the institution
    END FOR EACH
END DO
```

Table 1: Pseudo code of the computational model.

Appendix 2 – Simulation Toolkit



1 – control: The control panel is actually the most terrific feature in the Repast 3.1. simulation tool-kit. The control panel enables the possibility to jump through time in the simulation as you like, the only thing which is not possible is to go backwards. Here we can initialize, jump through time stepwise or continuously.

2 – parameter: Before we start with a specific simulation run, we can set the parameters individually. Obviously you will only find the most important parameters in this display, namely the size of the grid, the number of agents, the start value of the α, the memory-size and at last the influence parameter.

3 – display: In the display you can actually see the real-time dynamics of the model. There the agents move around the torus and build institutions or not.

4 – alpha graph: This graph is displaying the evolution of average societal trust.

5 – age graph: This graph shows the evolution of the average age of institutions. We took out the age of institutions as a kind of stability indicator of the whole system, so this is one of our basic target variables.
6 – agent graph: This graph displays the number of formal and informal agents per turn. So we get an overview where our agents are at the moment.
7 – action graph: The actions graph shows the share of cooperation at the moment. The green points visualize cooperative actions and the red one the defective actions. In sum they have to be one.
8 – inst graph: Last but not least the institution graph displays the average size of institutions per turn and the nominal number of institutions per turn.

Appendix 3 – The Effects of Memory Size on the Speed of Convergence

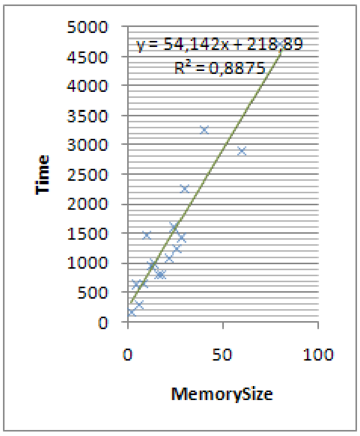


Figure A-1a : Scatter plot of convergence-time and memory size in a 20x20 grid with 100 agents (25% population density) and α_0=0.5

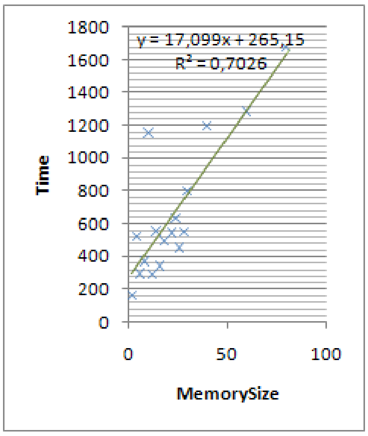


Figure A-1b : Scatter plot of convergence-time and memory size in a 20x20 grid with 200 agents (50% population density) and α_0=0.5

20x20 grid with 100 agents:

In Figure A-1a/b we tested the convergence time on different memory sizes on a bigger grid (20x20), on the one hand with a population density of 25% (Figure A-1a) and on the other hand with a population density of 50% (Figure A-1b). We expected that the density may change the results and give rise to other insights, but that assumption did not hold. The results show similar correlation in both cases, the only thing to mention is, as one can immediately see that the higher the population density the faster societal trust converges, which seems quite logical, due to the fact that agents meet more often in that case. But what the reader may not see is that a higher population density also needs more CPU power of the computer and consequently the runs last much longer.

Again the results show a high linear correlation with a calculated $R^2 = 0{,}8875$ and $R^2 = 0{,}7026$. It has to be considered that there were some runs where societal trust has not converged at the upper bounds with specific memory sizes. Therefore we excluded them from the analysis for reasons of robustness.

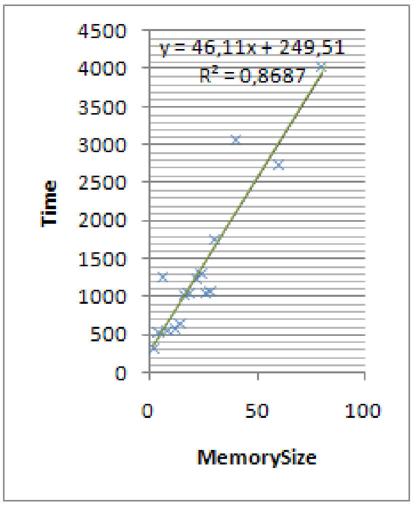


Figure A-2a : Scatter plot of convergence-time and memory size in a 30x30 grid with 225 agents (25% population density) and α_0=0.5

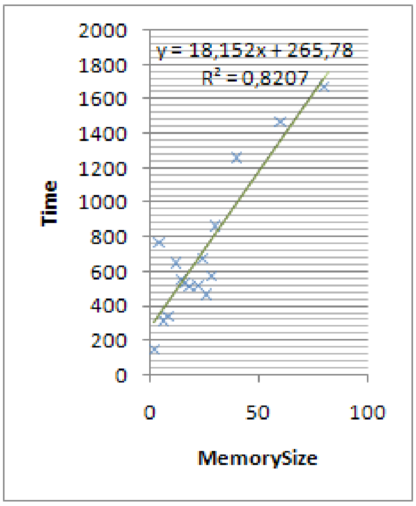


Figure A-2b : Scatter plot of convergence-time and memory size in a 30x30 grid with 450 agents (50% population density) and α_0=0.5

30x30 grid with 225 agents:

Again, as one can see in Figure A-2a/b the results hold in the tests. On the 30x30 grid with a population density of 25% we can calculate a correlation coefficient of $R^2 = 0{,}8687$ and with a density we get $R^2 = 0{,}8207$.

Hence, generally we can assume and have shown - according to the three case studies (including the one in the main text) - that memory size has strong effects on the convergence time of societal trust.