Coevolution of risk aversion, trust and trustworthiness: an agent-based approach

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ABSTRACT

The research presented here deals with the evolution of personality features of humans engaged in strategic interactions. The evolution of risk aversion and trustworthiness is modelled and simulated in the context of a binary trust game, seeking the origin and end-points of an evolutionary process, accounting for different degrees of locality.

This research has employed computer simulations in order to get dynamic equilibria in populations of players that keep evolving. The locality or global nature of interaction plays an important role. Risk aversion evolves together with trust and trustworthiness. Trust behaviour follows reciprocation attributes. Results of the simulations are equal to the ones elicited in empirical studies.

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Declaration: I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Jose Vicente Guinot Saporta

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CHAPTER 1. INTRODUCTION

Trust and trustworthiness can be highly significant in a society's economic and general development (Knack and Keefer 1997). There is a wide body of literature that connects trust with economic performance. Evidence suggests that higher levels of trust encompass greater levels of cooperation and financial health (Porta et al. 1997). Commercial transactions can be understood as actions of trust (Arrow 1972) and institutional success depends on the trust between institutions and the community (Putnam et al. 1994). Additionally, the competitiveness and welfare of a country's economy is related to the trust level in a society (Fukuyama 1995).

Conversely, untrustworthy or manipulative behaviour is often associated with antisocial people, which, in extreme cases, resembles the features of a self-interested and even psychopathic personality. It would be interesting to discover why, in an evolutionary context, psychopathic individuals can be fit and survive in a population under evolutionary rules affecting population dynamics over time.

The review of the relevant literature presented here regards the union of three interdisciplinary fields: psychology, economics and computer science. Psychology deals with the study of human traits and behaviours. These behaviours have also become the central theme for behavioural and experimental economics. Agent-based modelling (ABM) is a subset of modelling techniques which implement computational models of autonomous agents acting and interacting. ABM is a relatively new discipline which is based on and also nurtures many sciences such as biology, engineering, psychology, economics, finance, medicine and physics. Simulations are further explained in the next chapters. All these fields overlap with game theory. In Figure 1, we can see the connections among the disciplines involved in this study.

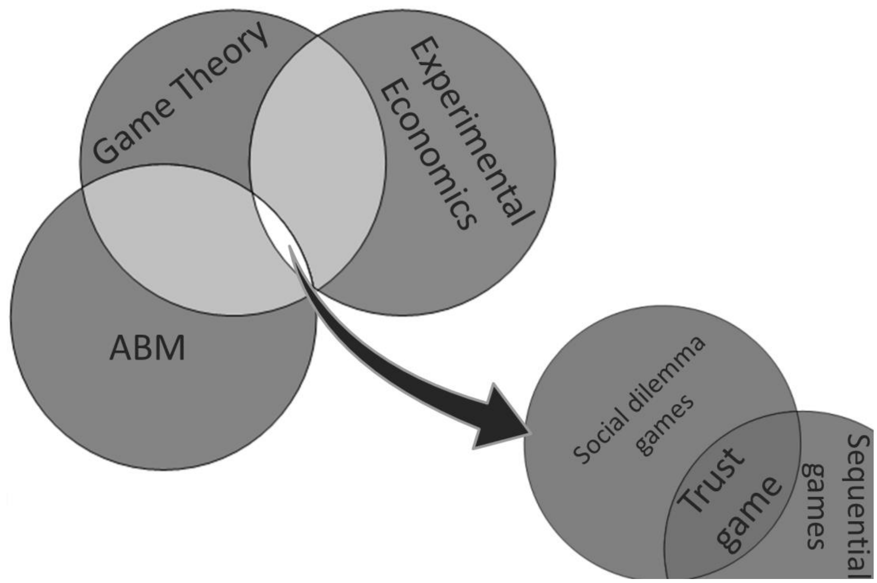


Figure 1. Interdisciplinary context of this research

Game theory is mainly focused on problems which involve cooperation and conflict between rational individuals, and adopt a mathematical approach with the necessary tools in order to study decision-making and conflicts (Myerson 2013). Mathematicians have always studied games involving probabilities determined by external factors (nature) occurring independent of players' actions, such as throwing a dice. However, games involving player skills and choosing strategies were described, formalized and improved in 1946 by von Neumann and Morgenstern in their book *Theory of Games and Economic Behaviour*. In fact, there had been earlier approaches, such as Cournot (1838), who interpreted players' decisions on their firms' outputs as strategically interacting duopolists, and Borel (1921), who described the minimax solution to zero-sum games. Game theory has played an important role in economics and other sciences, such as biology, politics, computer sciences, etc. The Nash equilibrium and the prisoner's dilemma games are now known to almost all social scientists. International politics in conflicts like the Cold War, Israel and Palestine or even the recent Ukraine conflict have been influenced or analysed through game theory by Nobel laureates Aumann and Schelling, among others. In particular, game theory has largely become the mathematical toolbox of the social sciences (Myerson 2013). In this thesis, an evolutionary approach to the trust game is adopted.

Studying the dynamics of social processes under the actions of evolving imperfect agents with simulations allows us to learn which initial conditions can lead to a specific result, instead of questions concerning what happens, or what might generally happen, under ideal conditions and full rationality (Gilbert and Conte 1995). Simulations allow us to make assumptions and generate data which can be examined by induction (Axelrod 1997). They combine the detail of qualitative methods and the rigor of quantitative methods. Using simulations is desirable because they deal elegantly with parallel, often complex, processes, making it easy to deal with agent heterogeneity (Gilbert and Troitzsch 2005).

Game theory and simulations are becoming central fields in computer science and have already become the inspiration for a prolific research agenda. In fact, these techniques have been applied to important research into such fields as virus interactions (Turner and Chao 1999), cancer research (Tomlinson 1997) or more picayune themes, such as organic food marketing (McCluskey 2000).

There have been different approaches to and applications of evolutionary game theory (EGT) simulations. In particular, many efforts have been made to understand the evolution of cooperation and reputation in games such as the ultimatum, the prisoner's dilemma and the stag hunt.

Evolution - based on Darwin's 'survival of the fittest' theory - does not explain all the diversity we find in human beings. Other theories can help us understand why this diversity exists, or how human evolution can be more or less affected.

The features of the approach adopted in this thesis are listed, and compared to other similar studies, in Table 1.

Table 1. Differences between our approach and existing agent-based approaches

Others agent-based simulations	**Proposed model**
Automata with 0 intelligence	Assumes two players: one intelligent (maximises utility function) and the other with zero intelligence.
Play always a pattern	One type of player endowed with a utility function to maximise each state of nature.
No coevolution (strategies nor traits)	Risk attitude/psychopathy coevolution.
Locality is exception	Focus on locality.
Simultaneous and symmetric games	Trust (sequential) game.

Three main gaps in the classical EGT, developed on the trust game, have been identified:

Gap 1: *Automata are 0-intelligence agents*.

Gap 2: *In typical evolutionary simulations, evolution affects actual "strategies", rather than an agent's "behaviour"*.

Gap 3: *Local interaction and trait similarities among neighbours have not yet been exploited.*

Figure 2. Concepts regarding novelties

In the approach adopted in this thesis, type 1 players act as maximisers of a utility function, whose parameters reflect the main traits evolving through replication across generations according to an agent type's success during the past periods of the game. Each era includes a number of encounters and consequent play in the game. Depending on an agent type's performance, an evolutionary algorithm is implemented to define the replication process, producing new mixtures of agent types and, consequently, the behaviour of new agents.

Agents of type 2 can be psychopaths, i.e. profoundly selfish and never reciprocate, or can be prosocial and always reciprocate. Not all the agents that do not reciprocate are psychopaths, there can be other reasons to not reciprocate. However we assume that all the psychopaths do not reciprocate. Therefore in a population with more psychopaths there are going to be less reciprocations.

We envisage a situation in which an agent's (type 1) utility function is characterised by a degree of risk aversion and another player's (type 2) trustworthiness. Following a sufficiently large number of eras, the initial population of both types evolve, leading to new distributions of agent types.

Population averages will be known in the beginning of each era, and they will be the values used to calculate the probabilities of being exploited or reciprocated in any given moment in this particular state of the society.

Meanwhile, agents of type 1 have a risk aversion parameter t, which will be modified thanks to a genetic algorithm (GA), depending on their fitness and their probability of being reciprocated p value, calculated in the beginning of each era from the number of psychopaths in the agent's neighbourhood.

Using the number of psychopaths in an agent's neighbourhood and a player's risk aversion, we define the player's optimal strategy in the game. Eventually, Player 2 will have to decide whether to reciprocate or not, depending on his strategy value.

As previously stated, the third gap in the literature relates to neighbourhood effects and similarity. Depending on the environment, humans take different decisions. For instance, players from Morocco trust Spaniards less than they trust the French (Georgantzis et al. 2018). A novelty of this project is related to this idea: traits are the elements whose consequences are behaviours.

The research to date has tended to focus on the observation of behaviours and traits with experiments and tests like the Self-Report Psychopathy scale (Paulhus et al. 2009). In the graph shown in Figure 3, we can see the typical frequency values of the people who have performed this test.

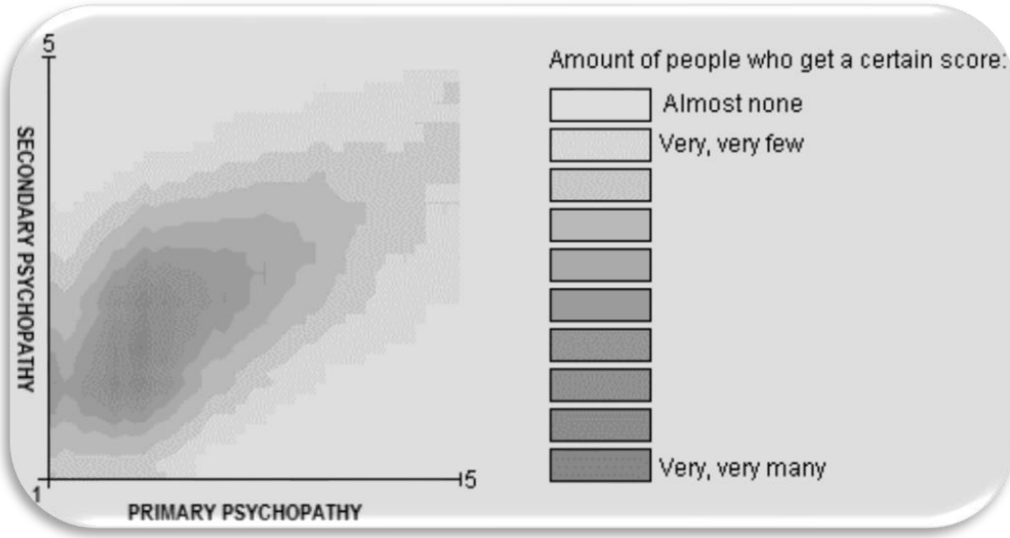


Figure 3. Primary and secondary psychopathy values obtained from a large subject population at the Laboratory of Experimental Economics, Jaume I University, Castellon, Spain.

Depending on the data collected from these experiments and tests, we can infer values for participating subjects. While these methods first observe behaviours and then elicit traits, our proposed research first characterises the trait and then studies the behaviour and its evolution.

Research in the field of ABM relates to both traditional and evolutionary economics (Jager and Janssen 2002; Tesfatsion 2002; Tesfatsion 2003; Hare and Deadman 2004; LeBaron 2006; Tesfatsion and Judd 2006; Tesfatsion and Judd 2006; Safarzyńska and van den Bergh 2010; Wendel and Oppenheimer 2010) and also to consumer-behaviour (Said and Bouron 2001; Said et al. 2002), but these models are too wide and the simulations use too many personality traits. These ABM simulations can be made simpler and more elegant to predict behaviour and give a new point of view on the evolution of trust.

In the unitary transaction, agents may have different roles; thus, they are not symmetrical. An agent is going to be 'Player 1' his whole life. In other games, such as the prisoners' dilemma, the two players engaged have symmetrical roles.

In computer science, there is a problem with some algorithms: once we run a program, we do not know if it is going to finish quickly, in an hour or never (Turing 1936). This problem is known as the 'halting problem'. To deal with this problem, a first approach is, after a reasonable time, to accept that the program is not going to finish normally. A halting problem also occurs with simulations: you never know whether, or after a hundred or a thousand eras, a population has reached an equilibrium. Even if one thinks a simulation is in equilibrium, there may still be these questions: Is it going to last? Is it going to be sustained if any disturbances happen?

Normally, equilibria can be characterised before the simulations take place. With automata, we can observe situations where the agents change but repeat some patterns. We would like to do this and know if we can get to same equilibria when we start from different initial conditions (Axtell et al. 1996).

One purpose of this study is to assess the extent to which simulations with local interaction among agents in the same neighbourhood and similar traits can emulate real experiments.

1.1. Thesis outline

The objectives of this research are: connecting economic theory, economic experiments and computer simulations; finding the evolutionary mechanisms for the emergence of prosocial/antisocial behaviour; studying how risk attitudes, trust, trustworthiness and reciprocity in the population affect mutually; testing these hypotheses with simulations; validating the results with empirical data.

This thesis consists of seven chapters. Chapter 2 contains the Literature review of this research. Papers related to economic theory, experimental economics, agent-based modelling and psychology are introduced in order to establish the foundations of this research.

Trust game (Berg et al. 1995) and a binary version of it (Bohnet and Zeckhauser 2004) are analysed in Chapter 3. A particular model of agent's behaviour in the Trust game is presented.

The results of the simulations based on this model are displayed in Chapter 4.

Chapter 5 discusses the findings of this research and future extensions.

Chapter 6 lists all the references and Chapter 7 contains descriptions and scripts employed in the simulations.

CHAPTER 2. LITERATURE REVIEW

This research presents a framework of human interaction involving trusting behaviour in which trustworthiness, risk attitudes and locality are embedded. The trust game (Berg et al. 1995) is used to model the basic features of trust and reciprocity among human agents. The basic setup assumes that individuals from two populations are matched in pairs to play a binary trust game. Thus, the simulations will emulate a binary-choice variant of the trust game, as implemented in the experimental setting by Bohnet and Zeckhauser (2004).

Human personality traits, such as cooperation, risk attitudes or psychopathy, can be viewed as relevant behavioural dimensions as proposed by (Hofstede et al. 2010). As a motivation for specific behavioural patterns, psychopathy can be considered an extreme personality trait corresponding to a ‘rational’, non-reciprocal behaviour as a second mover in the trust game (Georgantzis et al. 2015). In the following sections, the main findings in risk aversion and psychopathy traits regarding the focus of this research are summarized.

Decision-making can be modelled by artificial agents or autonomous decision-making entities, whose behaviour is approximated by simple rules regulating their actions (Sugden 2000). Inspired by spatial/geographical differences, simulated environments can reproduce experiments. Section 2.4 describes the procedures and methods employed in computational simulations and agents.

2.1. General introduction to evolutionary games

The trust game belongs to the family of social dilemma games. Social dilemma games are a specific type of game in which the cooperative solution – the solution that is best for the whole population – differs from the Nash equilibrium (Hardin 2009). Typically, the players in such games would individually get higher payoffs by making selfish decisions, which are collectively bad, and they get higher payoffs if they all cooperate, rather than if they all defect (Dawes 1980; Von Neumann and Morgenstern 2007; Myerson 2013).

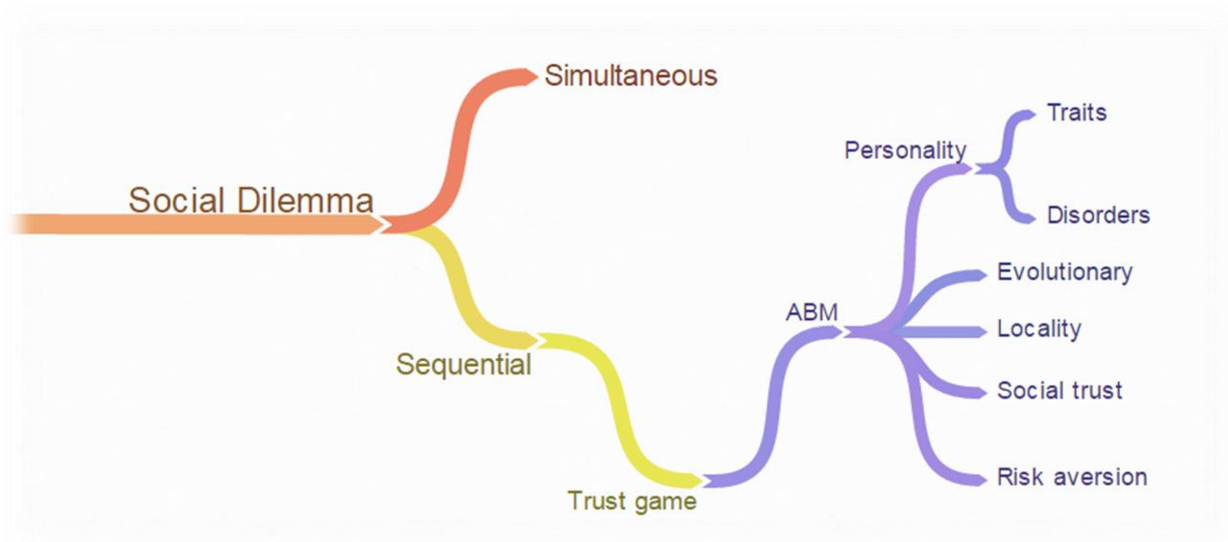


Figure 4. Ontologies of social dilemma for this research

This type of game can be used to address how to enhance or promote cooperation in the real world in important domains such as resource management and exploitation, population dynamics, pollution, etc. (Dawes 1980; Axelrod and Hamilton 1981). For instance, the use of pesticides and fertilizers generates a payoff to farmers which can be harmful to the population (Hayashi et al. 2010). Individual fuel consumption yields utility to consumers in the form of fast transportation or heating, but fuel consumption eventually causes pollution and fuel scarcity (Liebrand 1983; Cubitt et al. 2011). Social dilemma games can help us to understand and synthesize this kind of problem from a different point of view to laypersons and policymakers. Concepts such as cooperation, utility, individual decisions, trust, trustworthiness, reciprocity, reliability, freeriding, framing and resilience, together with other factors, have been studied in this field (Platt 1973; Rubenstein et al. 1975; Liebrand et al. 1986; Olson 2009; Attanasi et al. 2010; Cubitt et al. 2011; Sagiv et al. 2011). Among these games, this thesis focuses on the trust game, because it provides the simplest representation of trust and reciprocity among individuals (Berg et al. 1995).

Evolutionary game theory (EGT), developed by John Maynard Smith (Smith and Price 1973; Smith 1978; Smith 1982), is inspired by engineering, biology and economics and focuses on the dynamics of strategies in populations, rather than on the rational players and equilibria proposed by classic game theory. In EGT, players are not rational, they have strategies which they have as a heritage and will transfer to their progeny. Because of the complexity of the problem, EGT uses programming and simulation of games that are played repeatedly among autonomous agents, or automata, interacting in strategic situations. Depending on the distribution of behaviours over the population, some strategies are better from an evolutionary point of view, in the sense that they fit better (Hammerstein and Selten 1994; Hofbauer and Sigmund 1998). If behaviour changes over time, the most successful and, thus, more appropriate strategy will increase its share through an evolutionary mechanism (Friedman 1991). In such games, the relationship between the Nash equilibria (NE) and evolutionary stable strategies (ESS) has been identified. The concept of an ESS was introduced by Smith and Price

(1973) and mathematically formalised by Taylor and Jonker (1978), in order to help explain the dynamics of EGT. ESS is the conditional status of a population whose strategy distributions are not going to change once this point is reached, and can be understood as a dynamic equilibrium. In a dynamic equilibrium, players do not increase their expected payoffs by switching to another strategy (following the definition of a NE), even if their opponents change their strategies.

Therefore, in EGT, games are played in repeated interactions, where the main interest becomes the evolution of strategies (Khan et al. 2012). One-shot games can have non cooperative equilibria which deviate from those emerging in repeated games and real-world events. This has often been used to explain why cooperation emerges and is sustained in some contexts, instead of the NE corresponding to the one-shot game. Several such contexts exist and have been used to illustrate the emergence of socially superior outcomes as the result of players' forward-looking behaviour, such as in the case of deterrence theory as opposed to induction in the chain store paradox (Selten 1978). In an infinitely repeated or finite multiply-repeated game, players tend to minimise their maximum loss in the worst case (minimax). The folk theorem, or general feasible theorem (Myerson (2013), states that players can converge to mutual trust if they think that they have enough time, i.e. if the future matters (Friedman 1971; Cabral 2005) and any individual's rational decision can lead to a subgame perfect Nash equilibrium (SPNE) (Selten 1978). The latter is defined when, for every subgame, the restriction of these strategies is also an NE.

The existing research recognises the critical role played by social evolution and natural selection in repeated interactions of subjects. These studies observed the emergence of reciprocity (Trivers 1971; Axelrod and Hamilton 1981; Boorman 2012).

There are three different, but complementary, approaches in EGT research. First, the theoretical method described in previous paragraphs. The theoretical method relies on mathematical rules and logical premises. Initially, players were assumed to be fully rational and looking for Nash equilibria, until John Maynard Smith contributed to predict behaviours (Weibull 1997). Second, experimental methods are used to elicit the behaviour of 'boundedly' rational subjects in these games (Friedman 1996). The third method is agent-based simulation. Agent-based repeated game simulations obtain data from artificial subjects, also called agents or automata (Holland 1975; Binmore 1987; Kirman 1993).

Repeated trust games have been less explored in the context of evolutionary game theory, as compared to other games such as the prisoners' dilemma. In the next section, the literature on evolutionary trust games is reviewed.

2.2. Evolutionary approaches to the trust game

Social dilemma games share the common feature of juxtaposing cooperative and competitive behaviour. Thus, the literature on different evolutionary games can be used as a reference for the trust game. Laboratory experiments have systematically produced data which contradict the behaviour expected under the assumption of rational decision-making (Berg et al. 1995), whereas deterministic EGT has led to outcomes which are similar to those predicted under the classical economic solution concepts (Tarnita 2015).

Different elements can modify or explain the expected outcomes. For instance, with structured populations, noise and errors in the decisions can improve fairness (Rand et al. 2013). In fact, in a theoretical approach, Tarnita (2015) affirmed that stochasticity and mistakes increase the amount of trust and trustworthiness in a population.

Table 2 lists works related to this research by different features, such as the spatiality of the approach or the replication rules, that can be used as reference points. In the papers listed, there are theoretical or analytical approaches (Kimbrough 2005; Pacheco et al. 2006; Rigdon et al. 2007; Hauert 2010; Tarnita 2015). In other cases, data were obtained using experiments (Rand et al. 2013). Moreover, one of the most important tools in EGT is simulation (Nowak and May 1992; Macy and Skvoretz 1998; Hoffmann 1999; Page et al. 2000; Fang et al. 2002; Mui et al. 2002; Brandt et al. 2003; Roos and Nau 2010).

Focused on strategies performance, other repeated games have been simulated by computers. These simulations were oriented to the evolutionary fitness of populations of automata, with individual playing always one of the pure strategies available. For instance, cooperate (C), defect (D), tit-for-tat (TFT) and reputation TFT in the context of social dilemma games (Mui et al. 2002; Fehr and Fischbacher 2003) or the effect of the strategy known as R-wS (player chooses a safe decision if he won a previous lottery and a risky strategy otherwise) in lottery and stag hunt population simulations (Roos and Nau 2010).

Another aspect of this line of research regards the use of stochasticity and mistakes which affect the evolution of various strategies described by Nowak and Sigmund (1992). These hypotheses have been confirmed in computer simulations of repeated games such as the stag hunt game (Fang et al. 2002).

We can also find papers related to the evolution (arising) of cooperation in games such as the stag hunt (Kimbrough 2005), and theoretical evolution in some public-good games (Hauert 2010). Pacheco et al. (2006) studied the coevolution of network structures and strategies with symmetrical games.

Although some research has been conducted into risk and trustworthiness, the parallel evolution of risk aversion among type 1 players, together with the trustworthiness of type 2 players, in the context of the trust game has not yet been explored. The trust game allows us to study the parallel evolution of the two different parameters, each specific to a different agent-type engaged in this sequential (asymmetric) social dilemma. In this research, a continuous value for risk aversion is applied to the agents' distribution in the population.

Table 2. Papers related to EGT simulations or theoretic approaches

Author (year)	Methodolgy	Game	Reproductions	Strategies	Spatiality	Highlights
Mui et al. (2002)	Simulation	Prisoners' dilemma Snowdrift	No	AllC, AllD, TFT and reputation TFT	No	Measure the impact of reputation among agents in a quantitative approach.
Roos and Nau (2010)	Simulation	Lotteries Stag hunt	Imitate the best replicator dynamics	SS, RR, SR, RS, RwS, RwR	No	Simulation of risk aversion equilibria in binary trust. RwS is the best strategy in lotteries. RwS boosts cooperation in stag hunts.
Nowak and Sigmund (1992)	Simulation	Prisoners' dilemma	Frequencies proportional to payoff	AllC, AllD, TFT and GTFT GTFT generous TFT	No Round-robin, like Axelrod's tournaments	Errors in communications or decisions in heterogeneous populations. Suggests that generous TFT (GTFT) encourages cooperation that emulates forgiving. Stochastic instead of deterministic (y,p,q) probabilities to cooperate in the first round, after C and after D.
Page et al. (2000)	Simulation	Ultimatum	Proportional to fitness	Mutations S1 (p1, q1) p1 amount offered q1 amount threshold	Yes	Evolutionary setting enhances rationality. Spatial setting enhances fairness. For one-dimensional p = 0.5, two-

						dimensional p = 0.35. q is still small compared to experimental scores.
Rigdon et al. (2007)	Theoretic	Trust	Two-person experiment	In second treatment, more likely to play with similar.	Not directly	Can the cooperative play that emerged be sustained? Try to match in an experiment, players with reciprocators. ‘Since the SPE in our trust game is not a strict Nash Equilibrium, (R,d) is not an ESS.’
Tarnita (2015)	Theoretic	Ultimatum Trust	No	Weak selection	Structured	Uses weak selection and reputation in structured populations. Is more likely to interact with neighbours. Similar neighbourhood: geographic, strategic, genetic…
Rand et al. (2013)	Simulation and experiments	Ultimatum	New agent = 1-u reproduction OR u mutation	Mutations	Round robin	Stochastic EGT (errors in decision-making). ‘Finite population evolutionary analysis.’ Outcomes of simulations fit to the experiments.

Nowak and May (1992)	Simulation	Prisoners' dilemma	Substitution by the best neighbour	AllC, AllD, TFT	Yes	Introduces the idea of local interaction. Two-dimensional array.
Hoffmann (1999)	Simulation	Prisoners' dilemma	Yes GA matches random agents, mostly the fittest, random substrings of fathers and mutation.	32 automata 5-bit genes with one-round memory.	Ring	Local interaction and global learning. Interaction local learning global.
Macy and Skvoretz (1998)	Simulation	Prisoners' dilemma	Yes GA	15bits = genes	Yes	Use GA. Arising of behaviours: trusting neighbours more than strangers. Defector/co-operator, display marker, greeting, own intentions, attend marker, attend greeting, membership, trust neighbours.
Eckel and Wilson (2004)	Exp	Trust	No	No	No	No correlation between trusting and risk measures observed by Holt and Laury (2002) but inverse between reciprocating. Eventually, with a survey, they found a weak relationship.

Kimbrough (2005	Theoretic	Stag hunt	Imitate the best Learning in MLPS	Gridscape H & S MLPS	Gridscape	Gridscape model: two-dimensional lattice with non-intelligent agents. Markov learning in policy space with more intelligent agents. The supergame consists of a sequence of stag hunt games. Various games are an epoch. Trust emerges.
Brandt et al. (2003)	Simulation	Public good	Imitation. Replication and displacement.	Cooperate & punish Defect & punish Defect & don't punish Copp. & don't punish	Hexagonal lattice	Adding punishments reduces asocial behaviours. Less-cooperative individuals make more-cooperative societies. Each generation performed six games with two neighbours in each. Imitation can be understood as replication dynamics adapted to spatial simulations.
Pacheco et al. (2006)	Theoretic	Symmetrics Prisoners' dilemma Snowdrift	Pairwise comparison rule. Matching random, replace with probability = Fermi function (P=[1+exp(-beta(fa-fb))])	Co-operators Defectors	Build	Rational decisions. Build links and destroy if it is not productive.

Hauert (2010)	Theoretic	Public good	Replication dynamics	Contributors Selfish	No	Includes reputation and risk.

2.3. Evolutionary games with risk aversion

Over the past century, studies have provided important information on decision-making under uncertainity. Important milestones in the risk and subjective probabilities literature are ‘expected utility’ (Von Neumann and Morgenstern 2007), the Allais’ paradox (Allais 1953), risk attitudes (Arrow 1964), prospect theory and cumulative prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992), regret theory (Loomes and Sugden 1982) and rank-dependent expected utility (Quiggin 1982), among others. These theories and concepts are the foundation of new theoretical frameworks. They are widely applied, tested and used in decision-making experiments and simulations. The present research is based on expected utility theory.

Risk attitudes are commonly elicited in experiments with lotteries (Holt and Laury 2002; Sabater-Grande and Georgantzis 2002). Player 1’s role in a trust game can be interpreted as being equivalent to playing a lottery. Given that the first mover in a trust game may rationally choose to trust depending on his risk attitude and the probability of receiving a reciprocal investment from the second player (Fehr 2009), the evolution of risk attitudes becomes relevant for this study. Notwithstanding that Eckel and Wilson (2004) binary trust game experiments with risk measures found little relation between risk and trust. However, in these experiments, the Holt and Laury test was found to relate to reciprocation (risk-lovers were found to reciprocate less).

Risk-averse subjects reward pro-social players; hence, they promote cooperative behaviour (Hauert 2010). Roos and Nau (2010) simulated population dynamics in stag hunt and lottery games. They demonstrated that risky strategies make sense and can be beneficial in the evolution of cooperation.

This approach is related to how human traits evolve (Kirley and von der Osten 2014; Viossat 2014) in a framework that combines evolutionary ABM (Wu and Yanjun 2001; Manson 2005).

In experiments with cooperative significant payoffs and small groups of players, it was found that players move to a payoff-dominant strategy when games have two evolutionary equilibria: one risk-dominant (Harsanyi and Selten 1988) and one payoff-dominant (Friedman 1996). Risk attitudes may also evolve depending on genetics, social genetics or the environment (Harris 1995; Heckman 2006).

2.4. ABM simulations

Systems observed in the real world, from solar flares, animal migrations and climate change to the stock exchange, follow processes which have a complex mathematical basis. However, these dynamic systems have critically self-organized macroscopic behaviours, that is, their complexity can be reproduced with simple local interactions (Bak 2013). Abstract models and simple rules can capture aspects of the real world, such as complex behaviours or aggregated ones (Simon 1996). In these synthetic worlds, we can perform simulations with agents. These agents can work with isolated parameters and help us to understand complex problems (Alexandrova 2006). These ideas might be translated to the outcomes of repeated games, which are complex, whilst their rules can be simple. The way in which agents evolve and replicate in an evolutionary framework takes us to the beginnings of ABM (Kirman 1993; Axelrod 1997) with the modelling of ants or the dissemination of traits.

Social simulation is a subset of modelling techniques that are used in order to develop theories and conduct experiments which can be repeated in a way that would be not possible in the real world (Gilbert and Troitzsch 2005). Therefore, there are circumstances in which the use of simulations may be more appropriate than the use of closed-form solutions to usually simpler but tractable mathematical models in order to formalise theories in the social sciences (Taber and Timpone 1996).

This thesis intends to determine the extent to which a population's strategy evolution can be explained by simulations obeying genetic algorithms. Genetic algorithms (GA) are a type of evolutionary algorithm (Fogel 1966) that emulate natural selection due to embedded genetic rules such as mutation and recombination (Holland 1975). GA are useful calculating solutions or acceptable approximations to complex problems (Gilbert and Troitzsch 2005) and are applied in EGT. They make populations evolve and help them to reach ESS (Riechmann 2001). In these cases, agents are focused on performance (Vega-Redondo 1996). Replication dynamics were proposed by Hofbauer and Sigmund (1998) and consist of replicating the locally or globally fittest agents. A simpler method is the imitation of the best random strategy each time performance is compared (Matos et al. 1998; Tesfatsion 2001). Imitating the best method is one of the simplest criteria, where agents are imitating others strategies or are not following the Walrasian strategy (Vega-Redondo 1996; Vega-Redondo 1997).

In order to analyse games, we can use automata (Aumann 1981). After the first simulations with simple automata, such as in Conway's Game of Life, new ABMS appeared that were based on limited-strategies modelling (Deadman et al. 2000; Deadman and Schlager 2002). Kirman (1993) used ant behaviour in order to solve economic questions. Precisely, in the field of economics, Tesfatsion (2002) worked on agent-based computational economics (ACE) in order to describe economies with evolving systems of autonomous agents which interact among themselves (Tesfatsion 2003; Tesfatsion and Judd 2006; Tesfatsion and Judd 2006). Duffy (2001), in order to explain behaviour by real subjects, employed an expected utility function for easy decisions made by agents following a learned mechanism. Jager and Janssen (2002) built their agents with four strategies, one with utility maximization and the other three based on learning following different directives. Dal Forno and Merlone (2004) implemented agents with behavioural patterns elicited from experiments. Artificial populations constructed by them offered realistic results. Berger (2001) modelled different agents which had to adopt a new technology in agriculture. This agent had a profit function that had to exceed a threshold in order for the new technology to be adopted. Wu and Yanjun (2001) used repeated bids to elicit trust in an ABMS.

Computer science has evolved since the beginnings of ABM, raising the level of computational complexity following Moore's law, constrained by Amdahl's rule (Amdahl 1967; Moore 1975).

The first important reference to trust game modelling we can find is in one body of work by the first female Nobel laureate in economics, Ostrom (2009). Ostrom supports the idea that trust can be interpreted as a reaction to expected reciprocity. This model, adapted from a 2004 paper, is represented in Figure 5. It is inspired by human attributes such as cooperativeness, fairness, reciprocity and cooperation.

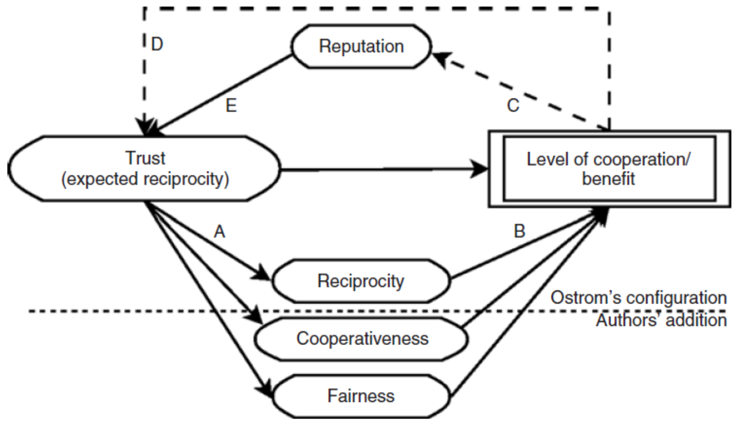


Figure 5. Ostrom's schema of her model (Ostrom 2009).

Another work related to ABM and ABMS based on Ostrom's model is the one performed by Ebenhöh and Pahl-Wostl (2008). Also, Ebenhöh (2006) has a chapter dedicated to trait approaches, known as 'the Big Five': openness, conscientiousness, extraversion, agreeableness and neuroticism. There is also an interesting work by Said and Bouron (2001), which models consumers within a traits-approach and applies GAs in order to calibrate the agent population.

There are more important features in evolutionary simulations, such as mutation factors and speed or strength of selection. Intuitivelly, we can figure out the purposes of these parameters. However, explanation of these features is beyond the scope of this thesis. We should mention that weak selection allows for more diversity in populations (Taylor and Jonker 1978; Taylor 1989).

One purpose of this study is to assess the extent to which social interactions are related to spatial structures, such as the model proposed by Schelling (1969). The model suggested in this research looks for explanations of aggregate behaviour following simple individual preferences and rules which may differ from social preferences (aggregate preferences).

2.5. Local interaction

Special attention will be paid to whether interactions are local or potentially global. On the basis of the locality or spatiality, the way people feel and behave within and across the borders of a country is both a cause and effect of phenomena such as social coherence, national identity or prosocial feelings (Burns 2006; Bornhorst et al. 2010; Hofstede et al. 2010; Hofstede 2011). For instance, we can appreciate the relationship between gross national product per capita and trust in different countries in Figure 6.

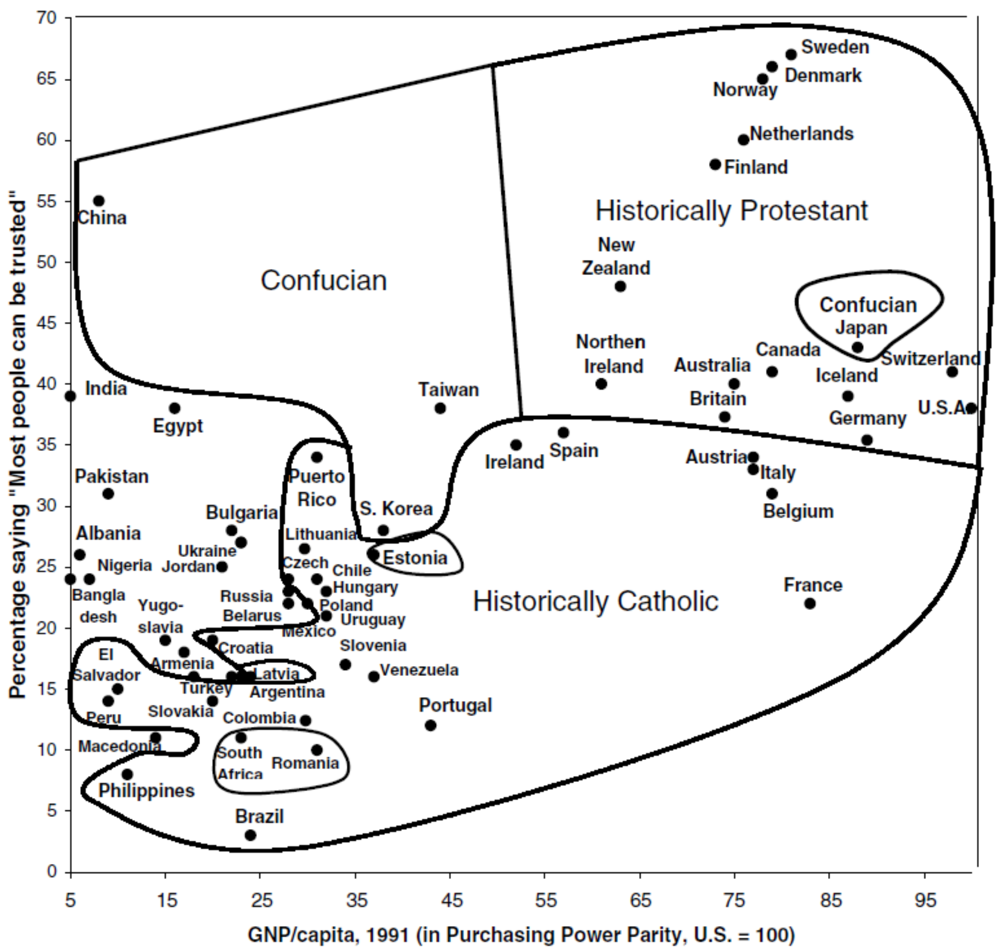


Figure 6. Cultural heritage, trust and economic development (Inglehart and Welzel (2005).

Decision-making in a game-theoretic setup within or between national or social groups has proved to be a valid tool for the identification of patterns of human behaviour associated with the proximity between, origins of, or distances among interacting agents. To this purpose, various experiments have been conducted using the trust game (Roth et al. 1991; Fershtman and Gneezy 2001; Willinger et al. 2003; Bouckaert and Dhaene 2004; Hennig-Schmidt et al. 2007; Akai and Netzer 2012; Georgantzis et al. 2018), showing how the behaviour and beliefs of individuals depend on their origin.

The spatial distribution of agents has been employed in many simulations to weight the probability of interaction (Nowak and May 1992; Nowak et al. 1994; Szabó and Tőke 1998; Hauert and Doebeli 2004). Lattice representation is one of the simplest methods and makes visual feedback easy to represent on paper. Examples of other EGT simulations, such as snowdrift and the prisoner's dilemma, are shown in Figure 7 and 8.

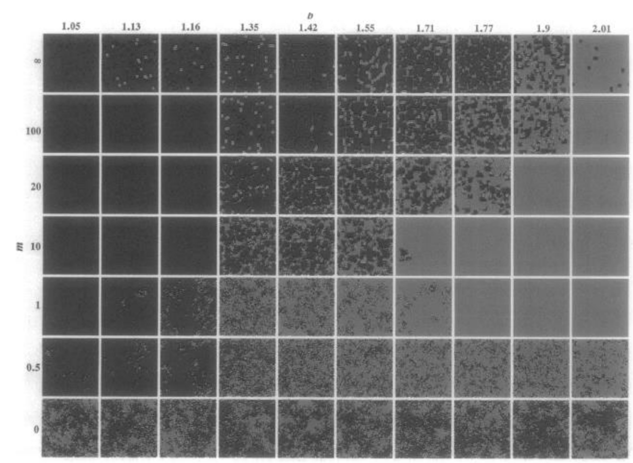


Figure 7. Lattices of 80x80 agents in a spatial distribution of co-operators (dark colour) and defectors (light grey) (Nowak 1994). Each column has a b value that is the payoff obtained by a defector interacting with a co-operator. The rows have different values for m, ∞ means that the neighbourhood is the best for the agent and 0 the worst.

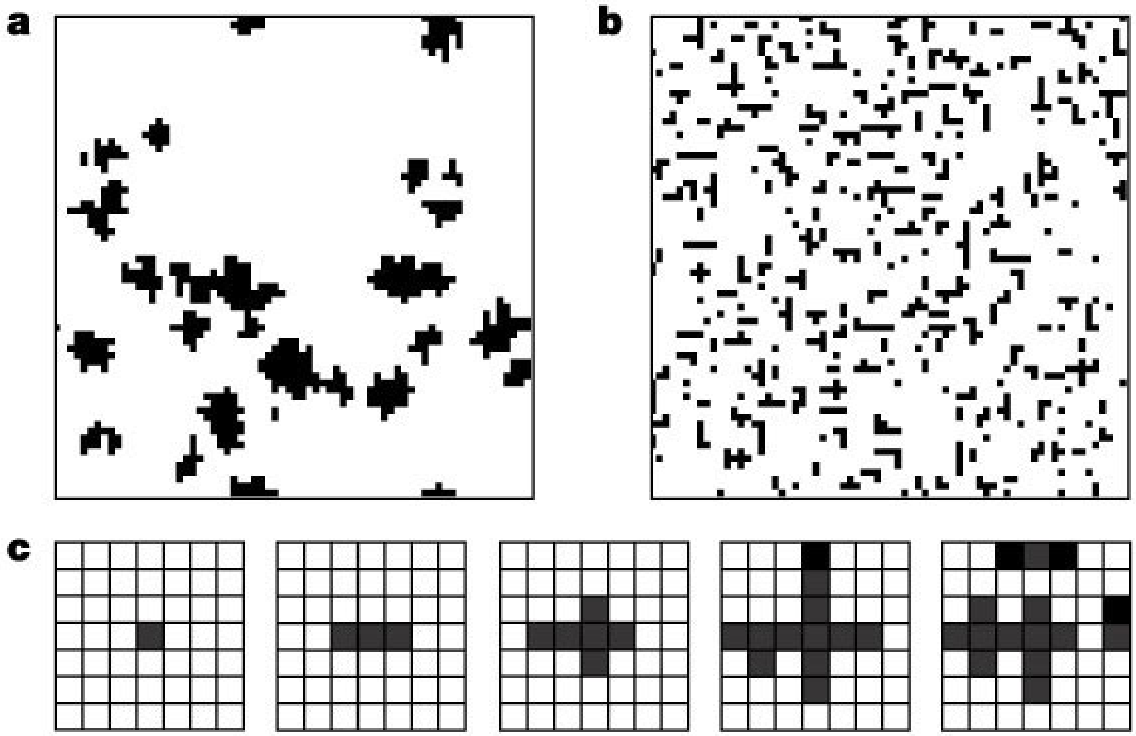


Figure 8. Clustering of co-operators(black squares) in prisoner's dilemma and snowdrift simulations (Hauert and Doebeli 2004).a) clusters of survivors in prisoner's dilemma. b) Isolated patches in snowdrift game. c) Detail, from left to right, of the creation and division process of a patch in the snowdrift game.

Several attempts have been made to model spatial considerations in population dynamics and ecosystems (Levin 1974; Levin and Paine 1974; Hastings 1993; Durrett and Levin 1994). In order to test these theories, the kinship of the subjects needs to be categorised. One characteristic, which can be easily categorised, is the nationality of the subjects. We can assume that nations are roughly clusters of humans who share some common idiosyncrasy, language and geography. Another way to cluster populations could be by religion. Instead of measuring distances between individuals by their nationality, we can use other dimensions, such as gender or religion, and their effect on risk attitudes (Miller 2000; Roth and Kroll 2007). For instance, we know that individuals from Muslim cultures are traditionally more risk-averse (Bartke and Schwarze 2008). Of course, there are many possible explanations to these phenomena, but it could be potentially reproduced, or at least approximated, in simulations with the approach introduced in chapter 3.

2.5.1. EXPERIMENTS WITH LOCAL INTERACTION

Many experiments and empirical studies that have collected data from games, including the trust game, have looked at neighbour effects on subject behaviour. They mostly study interactions within and across different countries. These are known as cross-country experiments and they have detected differences when subjects play with peers from the same or different countries. Research has also looked at the effects on trust due to similarities and differences within and across other social clusters, such as social class, culture and ethnicity (Fershtman and Gneezy 2001; Bouckaert and Dhaene 2004; Burns 2006; Bornhorst et al. 2010).

Strategies can be transmitted culturally by imitation or learning – the better the payoff of a strategy (cooperative) the better it spreads (Brown et al. 1982; Axelrod 1984). Repeated interactions in small groups lead to reciprocity of subjects (Boyd and Richerson 1988). This can be linked to local interaction. In this study, we will see if local interaction and imitation in simulations obey this principle.

Cross-country experiments with trust games have been conducted between Morocco, Spain and France (Georgantzis et al. 2018); Germany, Israel and Palestine (Hennig-Schmidt et al. 2007); Israel, Slovenia, the USA and Japan (in this case it was ultimatum game; (Roth et al. 1991); France and Germany (Willinger et al. 2003); and even on a huge pool of 23,000 subjects in the USA and Africa.

These experiments revealed that differences among subjects depend on their nationality. Some social behaviour has been captured in these experiments. Individuals playing with people from the same country trust more or less depending on the country they belong to. Moreover, when subjects are playing with subjects of a different nationality to themselves, trust levels differ. For instance, Moroccans trust French subjects more than they trust their fellow Moroccans. French subjects trust their fellow Frenchmen more than they trust subjects of other nationalities (Georgantzis et al. 2018). In order to study these theories, we should compare results between individuals playing with players who are related through geographic relation or locality with those playing with unrelated players.

2.5.2. AGENT-BASED MODELS AND LOCAL INTERACTION

This aspect, which is related to our proposed modelling strategy, regards the role of neighbours or the locality as opposed to the globality of pairwise interactions. We plan to match neighbours for a prisoner's dilemma game (Nowak and May (1992), but they will be given the option of only two strategies: cooperate or defect (always). In our model, Player 1 would sometimes trust and other times not, depending on his neighbours' reciprocity probabilities. Similar studies have also included spatial properties, such as hexagonal lattices for neighbourhoods, with reputation in public-good games (Brandt et al. 2003). In the terminology of Tarnita (2009), we want to implement structured neighbourhoods. Any agent can play with any other, but players will be more likely to play with their closest neighbours in the sense of geographic proximity, genetic similarity, strategies, etc. (Tarnita 2015).

Interaction among agents can be described in many ways. Given a population of agents, N, how many other agents can be reached by one specific agent, k? We call this 'neighbourhood of k' and we can name it N_k. So, inside a population there is a probability that two members are neighbours, i.e. this probability $q(i, j)$ is the likelihood of agent i to be able to play the trust game with agent j.

How agents interact among these neighbourhoods and get matched can be unstructured, but we are paying attention to more ordered systems. To make more intuitive or more realistic simulations, we can build in elements, such as spaces of n dimensions, where $n = 1$ is a linear world, $n = 2$ is a two-dimensional and $n = 3$ is a three-dimensional world. Furthermore, we can graph these simulations and we can even project higher dimensions and represent them. We can comprehend that agents that are closer to each other have higher probability of interacting and the higher the dimensions of the model are, the higher the number of neighbours of an agent can be.

Let us define distance d_{ij}, in equation (1). Let $path$ be a function which calculates the cardinality of agents belonging to a set defined by an initial, i, and an end agent, j, where all agents have at least one direct connection with any other agent belonging to the set. Distance d_{ij} is the minimum of neighbours that are between two agents, plus 1:

$$(1) \qquad if\ i \neq j\ then\ d_{ij} = min\big(path(i,j)\big) + 1$$

Where $d_{ij} = 1$ means that agents are direct neighbours and if $i = j$ then $d_{ij} = 0$.

Given an agent, we can define all the agents that can interact with this agent as 'the neighbourhood'. Formally, we will call $neighbourhood\ (k)$ the set of agents which can interact with an agent, k . It can also be called the 'window of negotiation' or *window*. In order to define a neighbourhood, we need to determine the maximum distance between the agent, k, and the furthest agent belonging to its neighbourhood. If we are talking about a two-dimensional, regular grid we can use the length of the side of the square area containing the $neigbourhood(k)$.

Let agent $j \in neigbourhood(i)$. Then, the probability of matching these two agents will be:

$$(2) \qquad q(i,j) = \frac{1}{cardinality(neigbourhood(i))} + \Psi(d_{ij})$$

$\Psi(d_{ij})$ is a weighting function, where closer neighbours have higher probability to meet. It can be positive for closest agents and negative for those further apart. If $j \notin neighbourhood(i)$, then $q(i,j) = 0$ and all the agents belong to the same neighbourhood.

These geometric properties can help us to vary the model to make it resemble different real-world situations. In Figure 9, we can see three examples of regular two-dimensional simulation representations. Von Neumann and Moore interaction neighbourhoods have been widely employed, and the last one is the hexagonal lattice neighbourhood used by Brandt et al. (2003).

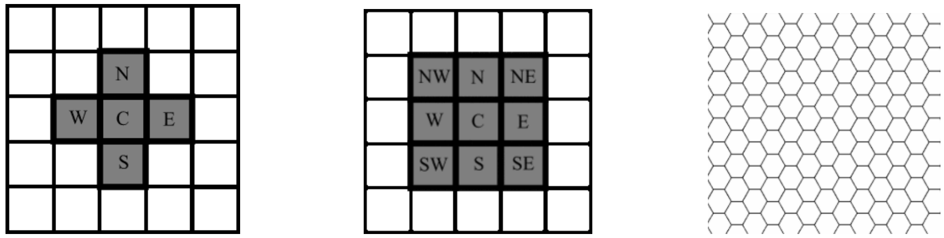


Figure 9. Examples of two-dimensional regular arrangements. From left to right: Von Neumann, Moore and hexagonal.

The complexity of an ABM social topology depends on the grade of detail necessary for its purpose. Nowadays, there is not a specific criteria and it is also considered an art (Schelling 1971; Axelrod 1997; Bonabeau 2002; Berger and Schreinemachers 2006).

2.6. Psychopathic personality and trust

There are many traits (possibly hundreds) which are used in natural language to describe personality traits, such as funny, aggressive, assertive, active, positive, cold, warm, shy, temperamental, sweet, focused, polite, selfish and so on. But psychologists agree that a review and combination of a small amount of principal traits is enough to describe a human personality (McCrae and Costa 2003). For instance, the Big Five, a combination of five characteristics measured in continuous values, is used to classify personalities (Goldberg 1990). The Big Five personality traits are openness, conscientiousness, extraversion, agreeableness and neuroticism. They have been found to correlate with certain behaviours in experimental games (Zhao and Smillie 2014). However, the research presented in this study is focused on other traits: psychopathy and risk aversion. Risk aversion has been discussed in previous sections.

Psychopathy is a mental disorder, popularized by movies, and is included in the DSM-V (Diagnostic and Statistical Manual of Mental Disorders V) as an ASPD (antisocial personality disorder), but it is also a personality trait that all humans have to a higher or lower extent. Psychopathy is characterized by behavioural patterns that include disrespect for social rules, low empathy, low inhibition, no regret, focus and courage. It is also known that psychopaths have low levels of anxiety or fear, that they mask maladaptive behaviours and are less prone to withdrawal and attention-seeking behaviours (DSM-V).

Psychopathy can be measured by many tests, such as the Self-Reported Psychopathy Scale-III (Paulhus et al. 2009). Higher scores on this test mean that the subject has higher psychopathy traits in his/her personality, but this doesn't tell us that this subject is a serial killer (Dutton 2012). It is common to find two other traits, narcissism and Machiavellianism, merged with psychopathy. These three traits are known as the 'black triad', which has been found to be advantageous in some ways to subjects and their communities (Dawkins 2006; Jonason et al. 2009). In fact, the lack of neuroticism and anxiety related to psychopathy allows subjects to get things done in adverse situations, which is often known as cold blood (Taylor and Armor 1996).

Some traits or disorders can have an evolutionary explanation to some extent (Bouchard and Loehlin 2001). Different non-functional mutations determine better IQ scores, memory, creativity or academic success. Nevertheless, the problem is that some combinations of these lead to disorders (Karlsson 1978). These correlations are highlighted in Table 3. In the case of psychopaths, one evolutionary benefit is that they take advantage of social elements such as trust and cooperativeness (Mealey 1995).

Table 3. Examples of traits or disorders related to exceptional abilities

Skills	**Trait**	**Paper**
Better IQ scores	disorders	Karlsson 1978
Creativity	schizophrenia	Kéri 2009
Academic success	psychopathy	Taylor and Armor 1996
Geniality	autism	Sacks 1998
Better memory	depression	Forgas et al. 2005
Mathematical ability	psychosis	Karlsson 1999

Antisocial behaviours may have many causes, including society, education, environment, biochemistry and genetics. The discussion into 'nature or nurture' (Plomin et al. 2013) is beyond the scope of this document. However, we can agree that, in some cases, genetics is associated with psychopathy (Blair et al. 2005). Neuropsychological deficits and determined brain area structures have been found to be related with psychopathic disorders (Beaver et al. 2012; May and Beaver 2012; Perez 2012). There are researchers who hold that this disorder is triggered by child abuse (Gao et al. 2010) and others who indicate that these traits are manifested in childhood (Hare 1999).

From the evolutionary point of view, there are studies that explain why unfavourable behaviours have a possible genetic motivation, such as the case of hyperemesis (pregnancy nausea or 'morning sickness'). Sherman and Flaxman (2002), proposed that hyperemesis occurs in order to prevent infections and toxins. Other authors point out that psychopathy is present in our gene pool possibly because cheats (i.e. not reciprocating people) can take advantage of their neighbours if the proportion of cheats is low enough (Frank 1988; Mealey 1995; Murphy 2006; Sachs and Simms 2006; Glenn et al. 2011). Furthermore, brutality can be useful to human groups in times of scarcity. In the ages before agriculture, laws, religion and governments the 'fittest' humans by natural selection were more prone to use violence, as they had no inhibitions, had their own rules and did not feel remorse (Hobbes and Curley 1994; Pinker 2011).

From an evolutionary perspective, psychopaths can affect the interactions between groups. Selfish behaviour can benefit the group with psychopathic members when these subjects have to allocate resources in their interactions with other groups, benefiting members of the 'in-group' (Brewer (1999). In fact, this benefit over the less-advantaged in-group members could be the reason for many of the war conflicts seen since the origins of mankind (Choi and Bowles 2007).

One of the purposes of this investigation is to explore the relationship between human traits and behaviours. As a result, the studies mentioned above allow us to infer that we can assume that human traits are related to genetic heritage and behaviours. Therefore, the model proposed in chapter 3 embeds these behaviours, which encompass psychopathy, risk aversion, trust and reciprocity.

2.7. Experiments and personality traits

A number of researchers have conducted trust game experiments with depressed and borderline personality disorder patients (Unoka et al. 2009; Wischniewski and Brüne 2013; Polgár et al. 2014)). Experiments with the prisoner's dilemma games revealed that non-cooperative behaviour is a source of higher gains for psychopaths (Mokros et al. 2008). It has been observed that psychopaths have lower acceptance rates in the ultimatum game and offer lower amounts in the dictator game (Koenigs et al. 2010; Osumi and Ohira 2010). In an iterated prisoner's dilemma game, high-psychopathy players defected more often and cooperated less (Rilling et al. 2007).

After running experiments with the trust game (Ibáñez et al. 2016), which studied the relationship between risk attitudes, cognitive ability, reciprocity and trust, the data analysis suggested that low reciprocity is significantly related with personalities that rated highly for psychopathy, disinhibition and impulsiveness. Moreover, Gillespie et al. (2013) affirmed that psychopathic people act selfishly and behave non-cooperatively in decision-making games. Table 4 shows some papers related to disorders and experiments.

Table 4. Experiments related to traits or disorders and different games

Trait/Disorder	**Game**	**Paper**
Borderline personality disorder	Ultimatum game	Polgar et al. 2014
Borderline personality disorder	Trust game	Unoka et al. 2009
Neuroticism and Machiavellianism, extraversion and openness	Dictator game	Wischniewski and Brüne 2013
Psychopathy	Prisoners' dilemma	Mokros et al. 2008
Antisocial personality disorder	Prisoners' dilemma	Montañés-Rada et al. 2003
Machiavellian egocentricity	Prisoners' dilemma	Curry et al. 2011
Psychopathy	Ultimatum game	Curry et al. 2011
Psychopathy	Trust game	Sabater-Grande and Georgantzis 2002
Psychopathy	Dictator game Ultimatum game	Gillespie et al. 2013
Machiavellian egocentricity	Ultimatum game	Spitzer et al. 2007

Experimentally, lotteries can elicit risk attitudes. Psychopathic personalities can be measured with self-reported tests. These two parameters are strongly related to this research, which is focused on trust and trustworthiness. Trust can be predicted with surveys (Fehr et al. 2003) and with the trust game.

2.8. Summarizing main aspects and gaps

This research combines game theory, psychology, experimental economics, ABM and computer simulation. This chapter has gone through the aspects needed to understand the whole research.

This thesis employs the binary trust game that is introduced deeper in chapter 3. Agents whose model is explained in chapter 3 were programmed and simulated.

In order to understand this model and the simulations that were made, the research done in the fields related to it needs to be outlined.

Evolutionary games have been introduced at the beginning of this chapter. Later the difference between theory and experiments has been highlighted with risk attitudes and experiments.

There is much less research related to simulations of the Trust game compared to the prisoner's dilemma. The sequential characteristic of this game, among the social dilemma games, makes it interesting and its simulation a gap in the research.

In the terms of locality, it has to be interpreted as something more than geographical distances. This model and simulations can be employed for any topological distance. The two dimensional spatial parameters employed in these simulations can be any couple of parameters of the agent attributes, such as: height, weight, blood pressure, agreeableness, neuroticism, extraversion, conscientiousness, openness, etc.

Circumstances such as society, culture, experiences and genetics affect human behaviour. Sections 2.6 and 2.7 give us an idea that there is something in our behaviour related with some disorders, there is something in our brains that builds our decision making mechanism and some features in excess can be a disorder in advanced societies (many of them are a problem only since the beginning of complex societies 8000 a.c.) but in other cases bring some advantages to the subject or even the group. Having an excess of one feature and the performance in a game has been explored in experiments.

Risk attitudes have huge literature in EGT and experiments. However there is nothing related to the co-evolution of risk attitudes and reciprocity so far. This is the main gap that this research covers.

This thesis analyses the coevolution of risk attitudes, trustworthiness and reciprocity through simulations of the trust game over generations of artificial agents that follow the decision-making mechanism described in chapter 3.

CHAPTER 3. THE TRUST GAME: AN AGENT-BASED APPROACH

3.1. The trust game: description

The trust game is a well-known sequential social dilemma game in which players take turns to make decisions. Whereas the prisoners' dilemma game has been studied broadly in experiments and in ABMS contexts, the trust game gives us a good opportunity to research a game which is sequential and comparable to the prisoners' dilemma game (Axelrod and Hamilton 1981; Wooldridge and Jennings 1995).

An earlier version of the trust game is known as 'the lending game' (the first player lends or does not lend; then if this player lends, the second player can pay back or renege), introduced by Camerer and Weigelt (1988), who employed it in their model of reputation. However, the trust game literature indicates that it was introduced as an investment game by Berg et al. (1995) and then it was experimentally tested by many authors (Burnham et al. 2000; Gambetta 2000; McCabe et al. 2001; Bohnet and Zeckhauser 2004; Ermisch et al. 2009; Costa-Gomes et al. 2014). The experimental outcomes, as happened with the prisoners' dilemma, contradicted the rational equilibrium prediction of 'no trust, no reciprocity'.

The structure of the game is as follows:

1. The experimenter gives an amount of money, d, to Player 1 (the investor).
2. Player 1 decides to secure an amount of money, s, and return some money to the experimenter $(d - s)$. If player 1 sends zero, then the game is finished.
3. Then the experimenter gives a larger amount of money $(b \cdot (d - s))$, to where $b > 1)$ to Player 2 (the trustee).
4. Player 2 decides which amount to secure $(b \cdot (d - s) - t)$ and how much to return (t) to Player 1.

In other words, Player 1 gets money, then decides to trust Player 2 (or not) and to send some money to Player 2. If Player 2 has been trusted, they receive a multiplied amount of money and decides how much to reciprocate following the trust from Player 1. We can express this analytically with the following equation (Tarnita 2015):

$$(3) \qquad T(S_1, S_2) = {}^{1}\!/_{2}\,(d - s_1 b t_2 + s_2 b (1 - t_1))$$

The strategy $S_1 = (s_1, t_1)$ means that subject one is going to send s_1 when he is playing as Player 1 and return t_1 when playing as Player 2. Subsequently, the expected payoff of a subject playing strategy S_1 versus another agent playing S_2, is going to be $T(S_1, S_2)$. This subject is going to play both roles and that is why you see a ½ in the beginning of this equation and then what he or she gets playing both roles is added.

3.1.1 BINARY TRUST GAME

The binary-choice trust game adopted in this research can be represented by the tree shown in Figure 10 and Figure 12. Retaining the notation and terminology of the previous chapter, we have two players, the investor and the trustee. In this game, instead of continuous values for the investor and the trustee, we have discrete values. Therefore, $d_{1,}, d_{2,} s_1, s_2, b, t_1$ and t_2 have discrete fixed values. If the investor (Player 1) decides not to trust, he secures d_1 and then Player 2 obtains a fixed payoff, d_2. For simplicity's sake, we will make these two amounts the same ($d_1 = d_2$). In the case that Player 1 decides to trust, he sends a fixed amount of money, s_1, and secures $n_1 = d_1 - s_1$. Then Player 2 decides to reciprocate with the maximum amount ($t_2 = m_1 - n_1$) or nothing ($t_2 = 0$). Hence, the values for the payoffs are fixed and they have the following relationship:

$$(4) \quad n_1 < d_1 = d_2 < m_1 = m_2 < n_2$$

These variables have a concrete value in the proposed model. More detailed explanation and figures on the trust game used on this research are provided later in this chapter.

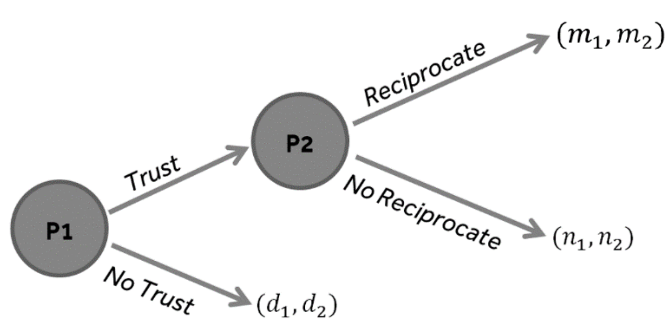


Figure 10. Tree schema of the trust game

We can forecast the strategies that each player would choose following the backward induction reasoning process: start with the last stage of the game and choose the optimal decision for Player 2, then do the same analysis with the previous stage and player given this decision. It would be: Player 1 notes that Player 2 is going to *Not reciprocate* if he *Trusts* her, so he chooses *No Trust* and Player 2 chooses *Not reciprocate*, although she knows already that he is not going to *Trust.* So, payoffs for this equilibrium are (d_1, d_2).

Table 5. Payoffs in the trust game.

		Player 2	
		Reciprocate	Not reciprocate
Player 1	Not trust	(d_1, d_2)	(d_1, d_2)
	Trust	(m_1, m_2)	(n_1, n_2)

Otherwise, if the game is sequential, we find a SPNE. Therefore, if we use backward induction, Player 1 is going to *Not trust* and the payoffs of this equilibrium will be (d_1, d_2).

3.2. Bayesian equilibrium of the trust game

type one players in this proposed binary game are not going to know the strategies of their counterparts. Moreover, they do not know their payoffs and, therefore, they do not have complete information. Nevertheless, they can have a belief of the strategy of their opponent. Let us suppose that players engage in repeated games with their neighbours and that, after some iterations, they can infer a probabilistic distribution of their payoffs.

Instead of thinking about a Nash equilibrium, we can use the beliefs of Player 1 to be reciprocated; that is, the probability that Player 2 is going to reciprocate. This equilibrium, that gives the beliefs of a player about other player, is known as a Bayesian Nash equilibrium. Therefore, the trust game is a Bayesian game because there is player information that is incomplete. If the utility of the *Trust* strategy is higher than the *Not Trust* strategy, then Player 1 will choose to *Trust*.

From the possible modelling alternatives, we assume a power function for the utility function, employed by Tversky and Kahneman (1992), ($U(x) = x^{\frac{1}{t}}$), linear weight of risk ($P(p) = p\ \ , probability\ of\ p\ is\ p\ itself$) and a constant error choice function, equation (5) (Stott 2006).

The main idea proposed in this approach is to describe the design and implementation of an agent's strategy with a utility function based on his belief of being reciprocated.

Let $p_{reciproc_i}$ be the *i*th agent´s probability of being reciprocated. Then, the expression $^1/_{t_i}$ represents the agent's risk aversion value unique to each individual r_i. We can see three kinds of risk aversion categories graphed from (Binmore 1992) in Figure 11. The parameter $t_i \in (0, \infty)$ will be greater than 1 if the subject is risk averse, 1 if the subject is risk-neutral and less than 1 if the subject is risk-seeking. The probability of being reciprocated ($p_{reciproc_i}$) is related to the number of reciprocators among the neighbours of the *i*th agent. Let's suppose that an agent plays with its neighbours with a uniform probability, the probability of being reciprocated would be the quotient of the number of reciprocator neighbours and the total neighbours. It can be also interpreted as a correct belief that could have emerged following a sufficiently long learning and Bayesian updating.

Then, each agent i (player type one) of the population acts in order to satisfy the following conditions:

$$(5) \qquad E(U_{trust_i}) \geq U_{not\ trust_i}$$

$$(6) \qquad E(U_{trust_i}) = p_{reciproc_i} m_1^{1/t_i} + (1 - p_{reciproc_i}) n_1^{1/t_i}$$

$$(7) \qquad U_{not\ trust_i} = d_1^{1/t_i}$$

$$(8) \qquad S_1 = \begin{cases} N & if \quad U(d_1) \geq p_{reciproc_i}\ U(r_1) + (1 - p_{reciproc_i}) U(n_1) \\ T & if \quad U(d_1) < p_{reciproc_i}\ U(r_1) + (1 - p_{reciproc_i})\ U(n_1) \end{cases}$$

Utilities U_{trust_i} and $U_{not\ trust_i}$ are going to determine whether agent *i* chooses the *trust* strategy if the former is larger than the latter. The risk aversion parameter initially follows a random distribution among the population of agents but becomes a discrete variable whose distribution is described as a histogram with a sufficiently fine grid. The expected utility of the strategy for the type one player ($S_1 = T$) $Trust,\ \ U_{trust_i}$ is composed by the utility of being reciprocated and the utility of not being reciprocated, each multiplied by its probability, according to equation (3).

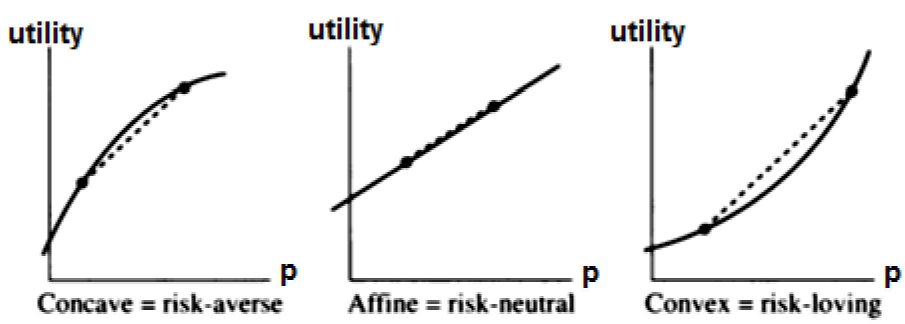


Figure 11. Utility function shape depending on risk aversion (Binmore 1992)

If we want to know what $p_{reciproc_i}$ is the one that makes an agent decide to change its decision we will need to look for p^*. For a set of fixed payoffs, it can be calculated changing equation (5) to an equality and so (6) equal to (7) then we extract $p_{reciproc_i}$ .So, there will be a p , equation (9) ,value that we will call $p^* \in [0,1]$, which is the threshold value that determines if Player 1 is going to *Trust*:

$$(9) \quad p^* = \frac{d_1^{1/t_i} - m_1^{1/t_i}}{n_1^{1/t_i} - m_1^{1/t_i}}$$

Trust is chosen by a player type one if his $p_{reciproc_i}$ is bigger (or equal) than p^*. Therefore, if p^* is close to 1, it is going to be difficult to *Trust* because in that case $p_{reciproc_i}$ has to be larger than p^*. Alternatively, if p^* is low or close to zero, it is going to be easier for *Trust* to emerge.

In order to calculate p^* we need to make the payoffs proportional (10) so the calculus of p^* (11) only has one incognita apart from t_i:

$$(10) \quad n_1 = a;\ d_1 = d_2 = 2a; m_1 = m_2 = 4a\ ; n_2 = 6a$$

$$(11) \quad p^* = \frac{(2a)^{1/t_i} - (4a)^{1/t_i}}{(a)^{1/t_i} - (4a)^{1/t_i}}$$

Because of the correct proportions on (10).Then p^*only depends on the risk aversion parameter:

$$(12) \quad p^* = \frac{2^{1/t_i} - 4^{1/t_i}}{1 - 4^{1/t_i}}$$

When a player is risk neutral $1/_{t_i} = 1$ then $p^* = 2/3$.

Each agent of type one is randomly matched to play the basic constituent game with another agent who is of player type two. With $a = 5$, the payoffs used in our model are shown in Table 6.

Table 6. Table of payoffs

		Player 2: Reciprocate	Player 2: No reciprocate
Player 1	No trust	(10,10)	(10,10)
	Trust	(20,20)	(5,30)

As mentioned in the introduction, type 2 agents will be "G" (good, always reciprocating, if trusted) or "B" (bad, never reciprocating, possibly due to an abusive, opportunistic or psychopathic personality). Psychopathy will be embedded in the population of type 2 agents by the proportion of "B" bad, never reciprocating, agents.

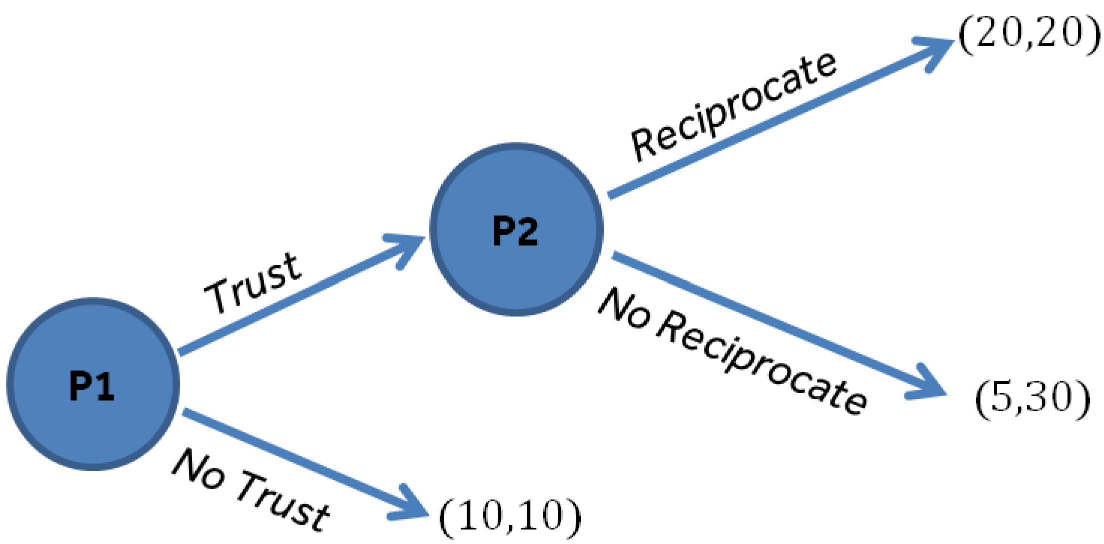


Figure 12. Tree schema of binary trust game with payoffs

In Figure 13, we can see a curve plotted in red, which we will call r^*, that lets us know which values of ${}^{1}/_{t_i}$ (y axis) lead to a *Trust* decision and which ones lead to a *Not trust* decision, depending on the $p_{reciproc_i}$ value (x axis). The set of values $({}^{1}/_{t_i}, p_{reciproc_i})$ under the line on the first quadrant are the set of conditions to *Not trust* for the type 1 agents. Notice the scales of the axis. Equation (13) is obtained from making equal the expected utility of *Trust* from equation (6) and the utility of *Not Trust* from equation (7) for a type 1 player with the payoff parameters from table 6.

$$(13) \qquad r^* = \frac{\ln\left[\frac{1-p_{reciproc_i}}{p_{reciproc_i}}\right]}{\ln[2]}$$

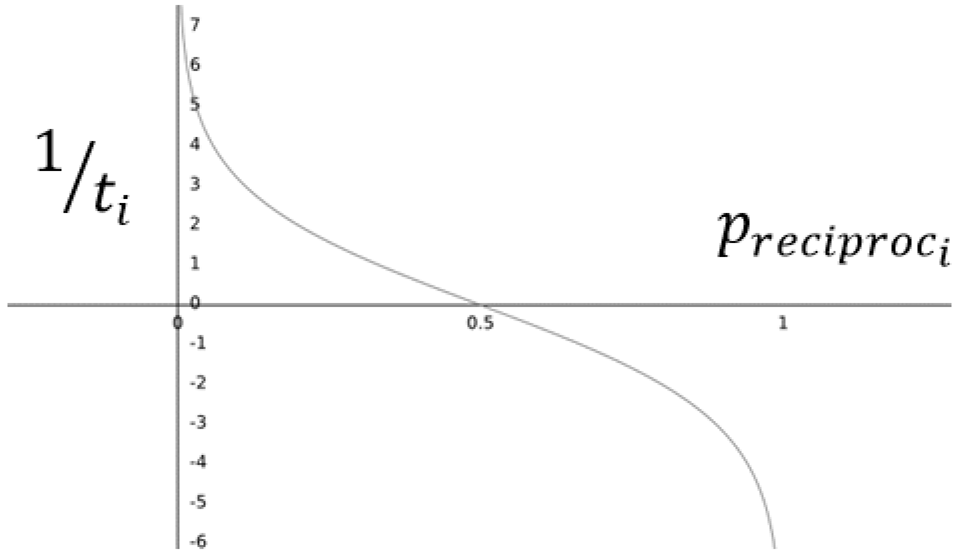


Figure 13. Hyperspaces of decision. $1/t_i = r_i$ is the ordinate axis and $p_{reciproc_i}$ is the abscissa axis.

3.3. Simulations

In our framework, it is assumed that the trust game is played by two different populations of agents: type 1 agents, who act as the first mover in each interaction, behaving rationally in order to maximize a risk-averse utility function; and type 2 agents, who act as the second mover in each interaction and behave like automata, each one endowed with a stable behaviour: “G” (good, always reciprocating, if trusted) or “B” (bad, never reciprocating, possibly due to an abusive, opportunistic or psychopathic personality). We will call the type 1 agents ‘intelligent’ or ‘non-zero intelligence’ automata to distinguish them from standard zero-intelligence agents.

Payoffs in a large number of transactions are used to assess the success rate for type of automata in the previous generation and proceed with the updating of the population composition in the next generation through a reproduction schema that we will introduce later.

Simulations have been deployed with agents distributed in regular two-dimensional lattices with a particular property of neighbourhood in the boundaries. It is a squared grid (mesh) with a toroidal topology. Agents in the top and bottom rows are considered as contiguous and likewise with agents of the leftmost and rightmost columns (Wilensky and Rand 2015). Neighbour interactions are Von Neuman's type (four neighbours per agent). Each simulation has lattices of 100 agents wide by 100 agents high, so the network size is 10,000. The replication dynamics is controlled by the accumulative payoffs of the agents when their fitness is compared. These comparisons can be made among members of the same neighbour or any randomly chosen member of the whole population, i.e. local matching and Panmixia (Laredo et al. 2008). All contiguous agents, after a number of iterations, are supposed to have had an equal number of encounters (Luthi et al. 2009).

3.3.1. EVOLUTIONARY SIMULATIONS

Simulations can be made given a set of rules and parameters. Repeating simulations many times for many different parameters can help find patterns and solutions to problems. In fact, given a hypothesis, simulations are commonly employed to demonstrate that there is a population (or a set of populations) with certain properties, which verifies this hypothesis. In other cases, we want to know what the outcome is if there is one change in the parameters of our model. In these situations, the calculi of all the possibilities can be really difficult or computationally unbearable. Moreover, because of the nature of this research, we look for possible initial populations that can lead to EES populations obeying our model and the feasibility that EES populations can be obtained following our model. Nevertheless, reaching these ‘final’ populations (EESs) requires them to be smooth and based on individual changes; they cannot be achieved by unexplainable jumps. Therefore, in order to find solutions in an efficient way, evolutionary rules are employed to make populations evolve in our simulations (Blume and Easley 1992; Holland 1992; Axtell 2000; Boschma 2004).

Just as in natural environments, individuals of a population interact with their environment and ‘perform’ better or worse than other elements of the population. Evolutionary artificial agents follow rules of replication dynamics (Conte et al. 2013). Therefore, the population changes from the original one to a new one which ‘moves’ towards its ‘destiny’, given the original population.

3.3.2. INTRODUCTION TO THE CHARACTERISTICS OF THE SIMULATIONS

We chose an initial population, where type 1 players have a probability of 50% to *Trust*.

We have calculated that, for a value of $p = 0.25$, the frontier value of t is 1.58. It can be the central point of a distribution of players (a rectangular area containing the dot in the line of Figure 14) in a population in order to obtain good heterogeneity.

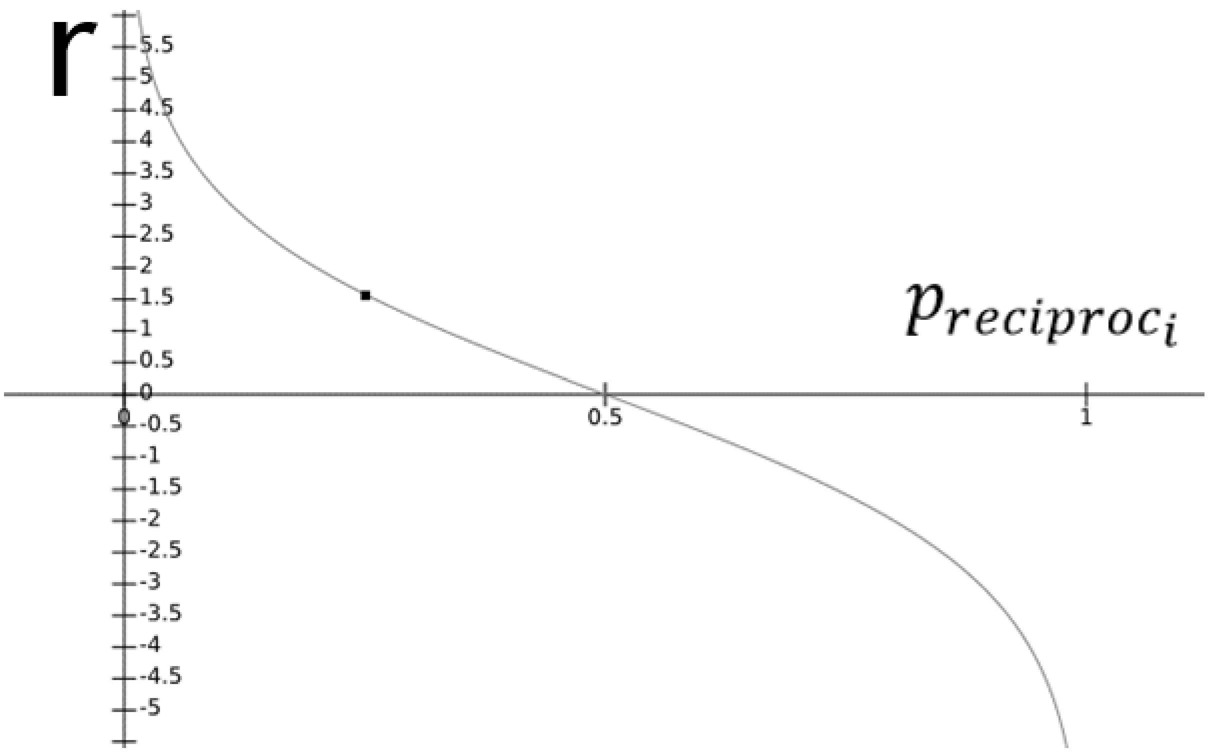


Figure 14. Values of $r_i = 1/t_i$ depending on the probability of being recirpocated. The line splits the space into *Trust* and *Not trust* strategies.

In Figure 15, we can see the values of different functions which correspond to the utility expected for five possible situations: 0% of reciprocators surrounding the agent, 25%, 50%, 75% and 100%. Notice that axis *y* represents expected utility and axis *x* is the $1/t_i$ value, and that they are conveniently scaled. In this case, only with a value of 0.25 does the value of $1/t_i$ have to be taken into acount. For values higher than 1.58 (very risky agents) and p = 0.25, all player 1 agents *Trust*.

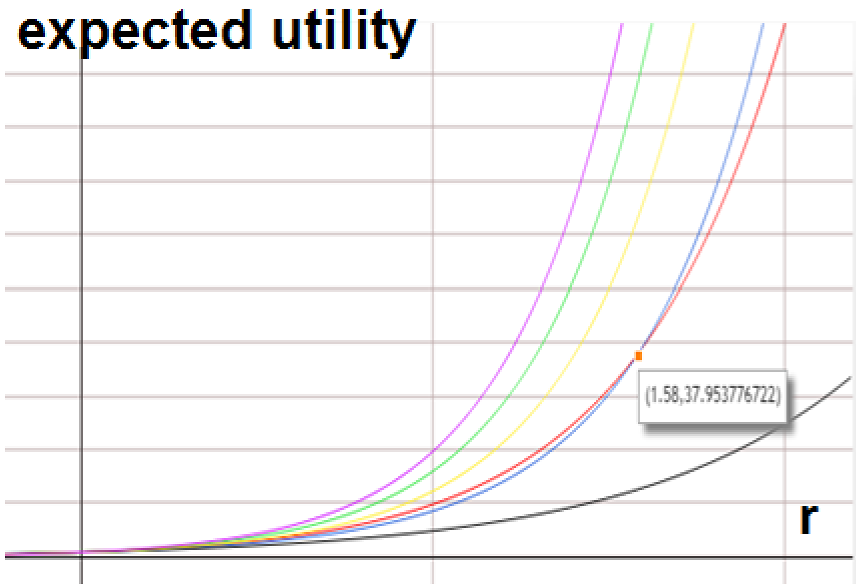


Figure 15. Expected utility of six possible scenarios. Representations with different probabilities of being reciprocated (0, 1/4, 1/2, 3/4, 1) and trust

10^r $\frac{1}{4}20^r + \frac{3}{4}5^r$ 20^r $\frac{3}{4}20^r + \frac{1}{4}5^r$ $\frac{1}{2}20^r + \frac{1}{2}5^r$ 5^r

3.3.3. PARAMETERS AND RULES

We will simulate the game with initial populations of agents with different characteristics. Firstly, populations with a high probability of being reciprocated (many Player 2 reciprocators) will play the game among themselves. In second place populations, with low a probability of being reciprocated (many psychopaths), we will do the same. Eventually, a population with values observing proportions of one reciprocator out of two, or four type 2 agents, will interact among them.

Besides the proportion of reciprocators in the population, the values of r among the population will be uniformly distributed randomly between the ranges of [0, 3.2], [0-1] and [1-2], suggesting heterogeneous societies, risk-averse populations and risk-loving populations. Moreover, as we will see in Section 3.3.3., that initial population of type 1 agents will be spatially ordered. Figure 16 shows two examples of different populations expressed with colours and a third dimension (correlated with values).

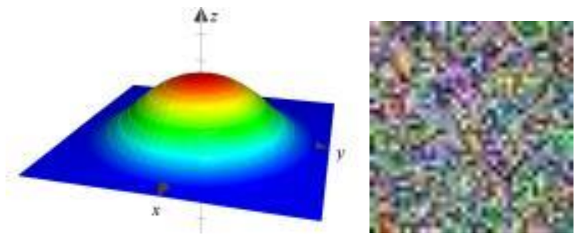


Figure 16. Uniform and randomized spatial distribution

Evolution of the populations can follow any of the rules described in Table 7.

Table 7. Rules of evolution for risk attitude and reciprocity

Evolution	Reciprocity evolution
• No changes	• No changes
• Only swap	• Only swap
• Matching partner for comparing	• Matching partner for comparing
○ Locally	○ Locally
○ Bigger neighbourhood	○ Bigger neighbourhood
○ Globally	○ Globally

3.3.4. EXAMPLE

In Figure 17, an example of initial and final values of r, risk attitude detailed in section 3.3.3, in the population of type 1 agents is shown. Values of r go from 0 to 3.2. A risk-lover agent will have an r value greater than 1, a risk-averse agent will have an r value lower than 1 and a risk-neutral agent will have a r value of 1. Population of type 1 agents is shown isolated from type 2 agents. There is a loss of diversity of the r value because there is no mutation in this example, but risk-lovers can be found in a population which is risk-averse on average. In Figure 18, type 2 agents in the same simulation are shown. In both cases, spatial entropy in the final generation is lower than in the initial one. Agents tend to be clustered in patches of population with same attributes.

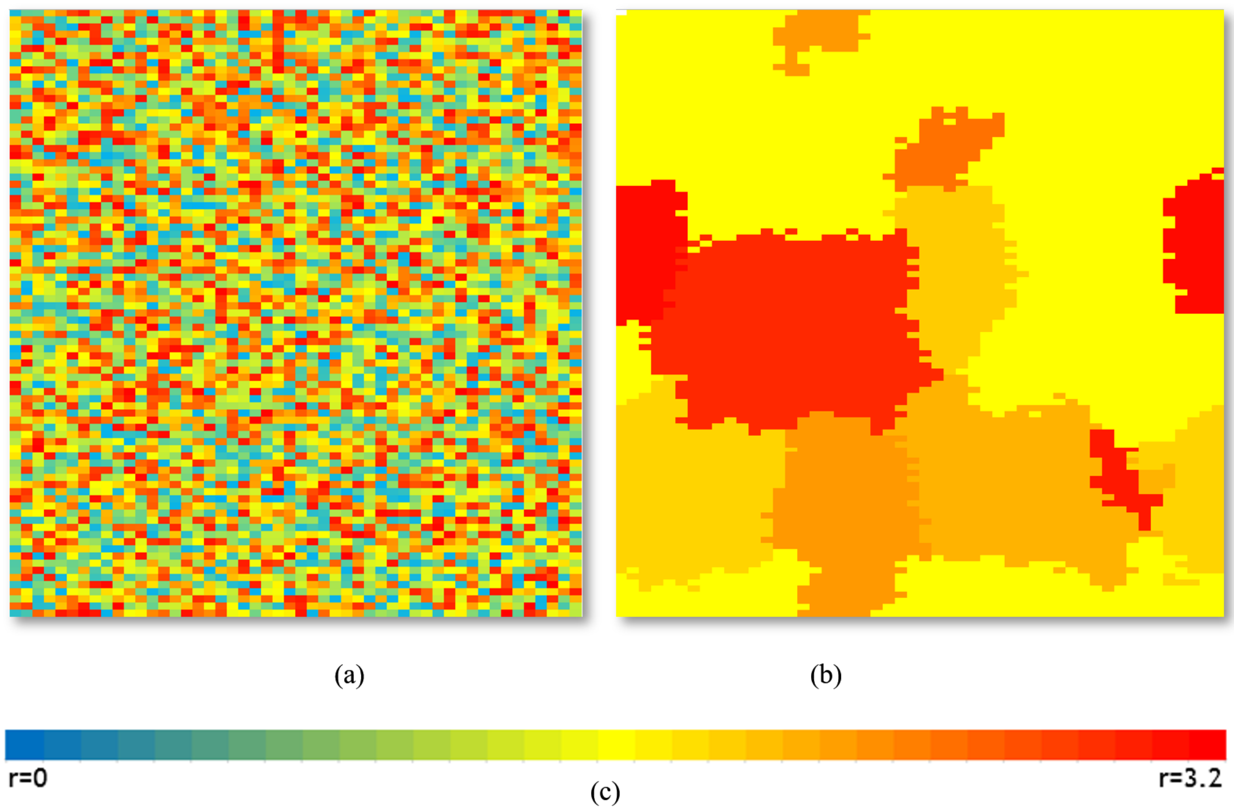


Figure 17. (a) Initial values of risk attitude (b) Values of risk attitude after 10000 generations (c) rank of values for r

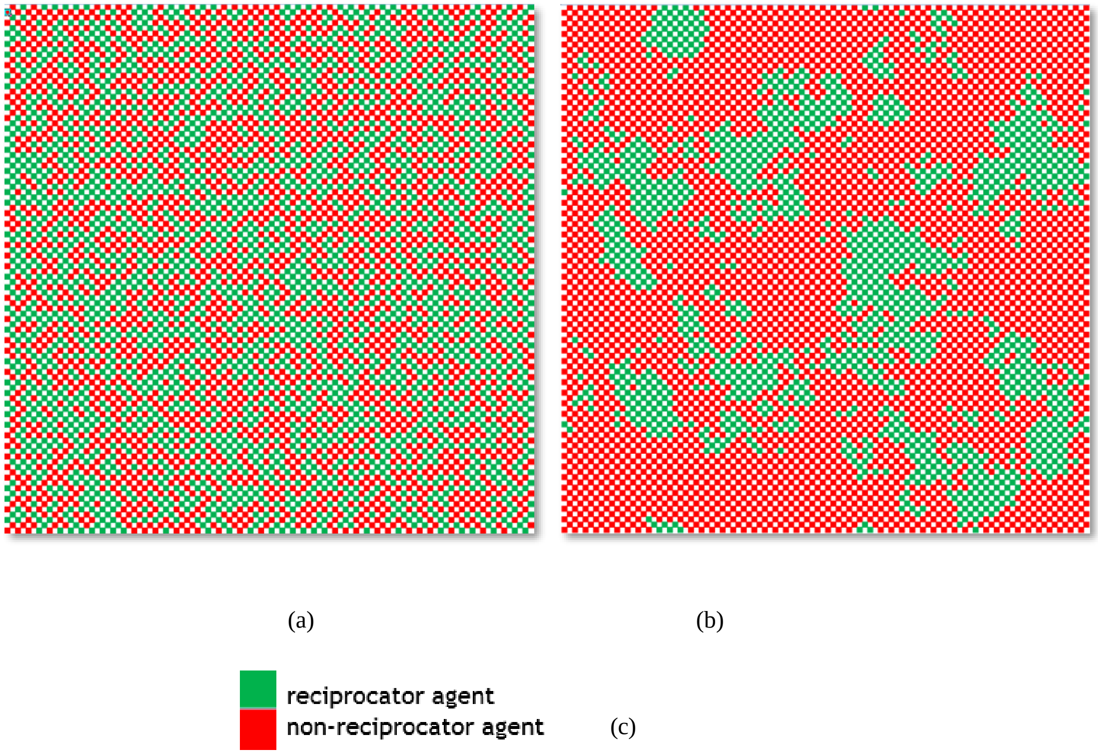


Figure 18. (a) Initial population of type 2 agents (b) Final population of type 1 agents. (c) Colour legend.

3.3.5. SPATIAL DIMENSION

We already have explained that the agents are arranged in a regular lattice with interactions in a Moore neighbourhood. Because of the nature of these interactions and the asymmetry of their roles, the agents are arranged in specific positions. The agents are distributed in a way that every agent is surrounded by four agents (to the north, south, east and west) with his/her opposite role, like on a chessboard, where black squares are type 1 agents and white squares are type 2 agents.

Simulations will show characteristic clusters as shown in the example in the previous section.

3.3.6. GLOBAL VERSUS LOCAL IMITATION

In this section, we analyse whether there is any difference between global and local imitation. In their day-to-day interactions, humans compare their strategies/actions and outcomes with the other members of environment. Usually, the closest 'environment' is the people a human can compare their performance with, i.e. neighbours, siblings, and family (Case and Katz 1991; Visscher 1998; Mazumder 2008). However, in some cases, they can pay attention to other humans that are not in their closest environment, such as chieftains, foreign visitors, competitors of other tribes, kings, philosophers, business men, religious leaders, football players, etc. The imitation dynamic follows this principle and we will see if there is any difference.

At first sight, we can think that local interactions can disseminate a characteristic among a population in the long term. However, depending on how fast these strategies are expanded, competing with third strategies can have a different outcome. For instance, a strategy can be blocked by other competitive strategies (Arthur 1991; Blume and Easley 1992) or it can succeed in other places, interacting with other strategies, compatible or synergetic (Schöner and Kelso 1988).

3.3.7. SHOCKS AND MUTATIONS

In this section we will mention the idea of introducing mutations in the parameters and exogenous shock affecting payoffs in the simulations.

During the 'tulip mania' of 1635, the Dutch population imitated their compatriots who had sold tulip bulbs for high sums. Some of these bulbs showed profits that were a hundred times the typical salary. Consequently, many Netherlanders stopped their main occupation and had started to cultivate and trade tulip bulbs. Unfortunately, in 1637, the value of the bulbs went down and produced the first financial bubble (Mackay 2015).

What happens when the utility function changes? What happens if something that was valuable is not valuable anymore? What happens when there is a technological improvement that shakes the market? What was the impact on the population when humans first learnt to manage fire?

By changing the payoffs, shocks are embedded in the simulations. Essentially, the payoff is changed when a population is in an ESS. Therefore, resilience and robustness of equilibria are tested with these shocks.

Heterogeneity of r

You could think that an average value of 0.8 means there are no risk-loving agents, or that there is no heterogeneity. Here, in Figure 19, we can see that we keep heterogeneity and that there are risk-lovers. Keep in mind that this simulation has no mutation. The evolution of populations of type 1 and type2 agents, ending with this average value of 0.8 for r, are represented in Figure 20.

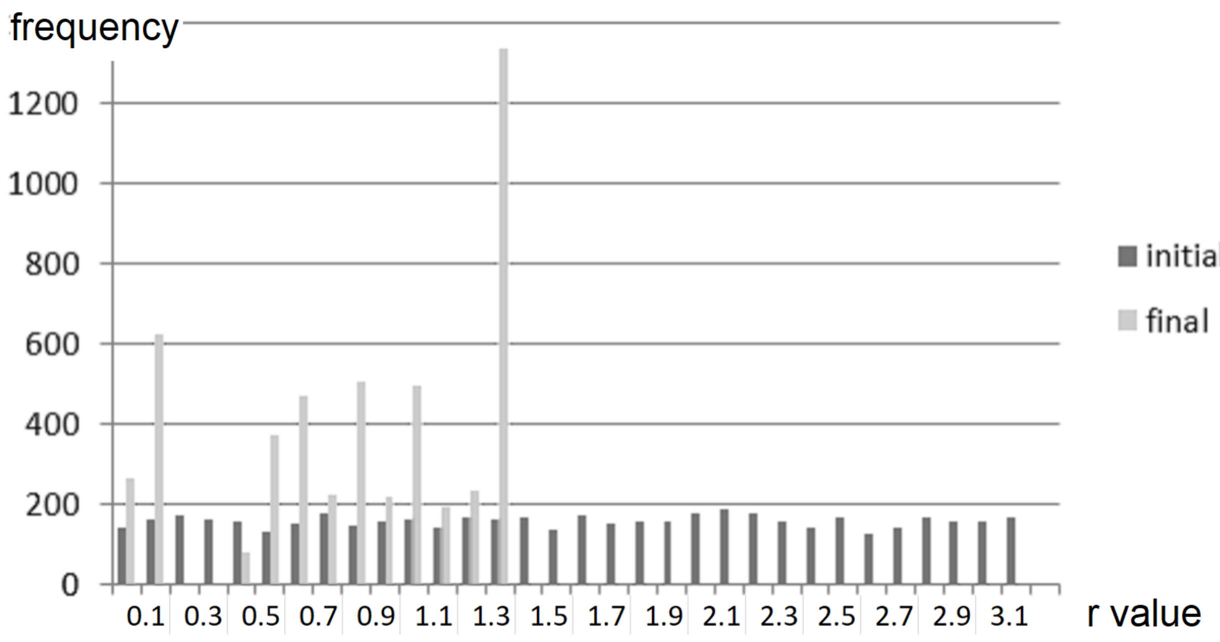


Figure 149. Frequencies of r values in the initial population (dark grey) and final population (light grey). Values clustered in 0.1 intervals.

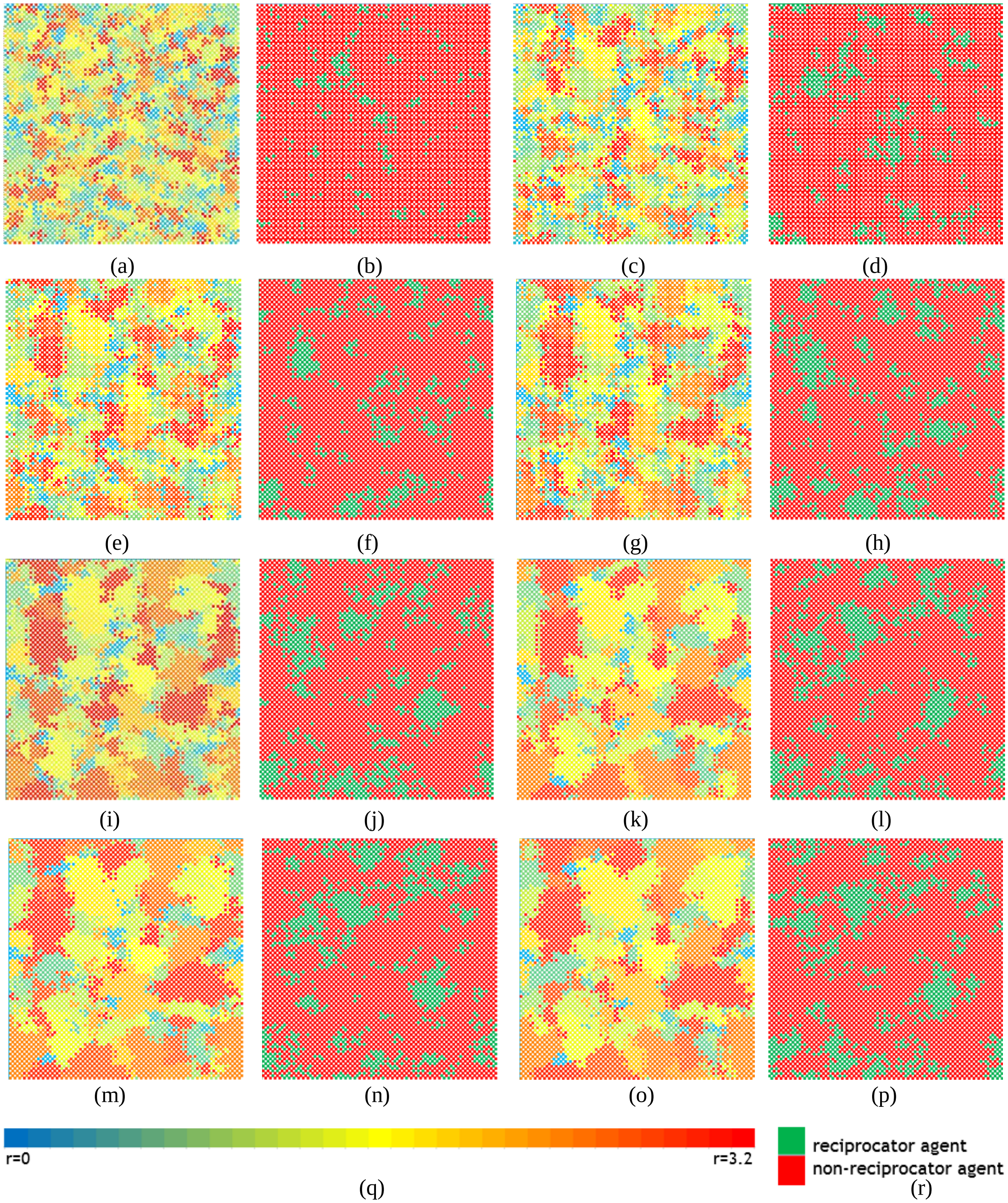


Figure 20. Evolution from left to right and up to down of type 1 agents (a,c,e,g,i,k,m,o) and type 2 agents (b,d,f,h,j,l,n,p) agents with 10 generations of evolution shown. Populations (a) and (b) evolve 10 generations in till they get to (o) and (p). (q) and (r) are the possible values represented.

CHAPTER 4. RESULTS

Simulations were conducted using FLAME (flexible large-scale agent-modelling environment) software. FLAME is a generic agent-based software which can be used for many different purposes and it was designed to be compiled and executed in many different computers, from regular desktops to HPC (High Performance Computers) supercomputers. It enables the researcher to run simulations in parallel in order to take advantage of multicore computers with a very interesting flexibility. Flame was developed for the European project Eurace (large scale macroeconomic agent based model), well known computational economist worked in it. Its flexibility on the parallelism, the possibility to escalate the execution of the simulation on larger computers without changing the code and experts in the field behind the project are the reasons for using Flame in this research.

For instance, it takes six hours to run six parallel simulations of 10,000 generations in a Xeon computer with eight cores. So, six cores are busy for six hours and two other cores are available to work on other duties. In other computers, with fewer cores in their processors and lower clock frequency, it takes up to 30 hours for each computer.

In order to enable parallel computing execution of the simulations, FLAME operates messages between agents. These messages are broadcasted (synchronously) to all the agents and they are capable of reading them all.

Very briefly explained, agents have an individual memory that keeps variables which go through different sequential states (from start to end) and have functions that, given the inputs from messages and memory-generated outputs to messages, change in the state and change in its memory.

You can appreciate the diagram of states (rounded shapes), functions (squared boxes) and messages (green boxes) of Player 1 and Player 2 of the simulations in Figure 21.

All simulations performed have 100 per 100 lattice agents. Agents are arranged as a chessboard with type 1 and type 2 agents.

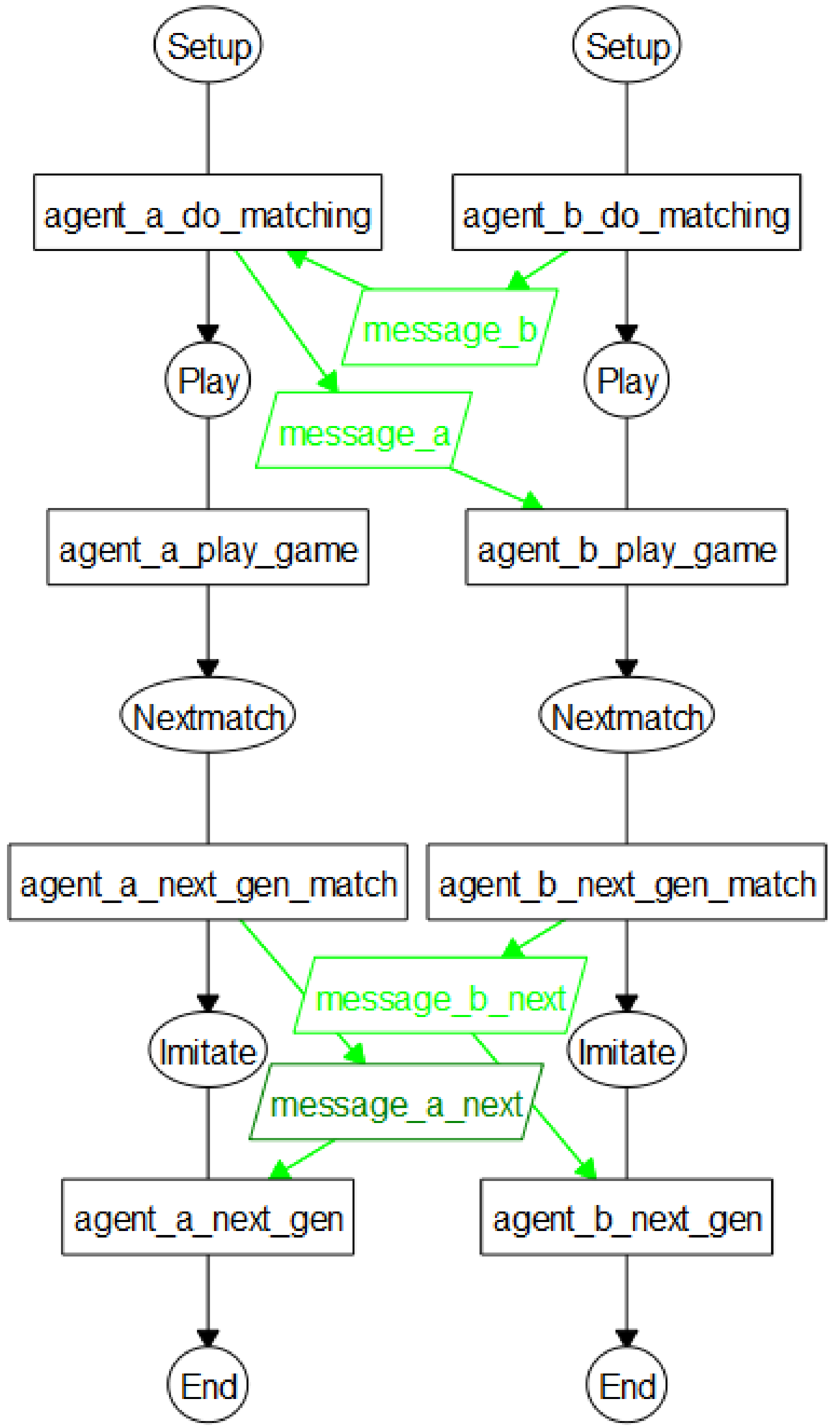


Figure 21. State diagram of agents. Player 1 on the left and Player 2 on the right.

4.1. Trust is clustered in wealthy neighbourhoods

In Figure 22, we summarize the results from simulating 10,000 generations. Type 1 agents swapped randomly their r value with their neighbours the whole experiment. All type 1 agents have a value, r, which is uniformly distributed between 0 and 3.2 and randomly spatially distributed, as represented in Figure 23 by different colours (average value is 1.604). Meanwhile, in each iteration, type 2 agents compared their performance with their closest randomly chosen neighbour and imitated their strategy if their performance was better. That is to say, local agents imitate the best as we mentioned in Chapter 3. Before simulating coevolution it may be worth to analyse what happens when only one parameter evolves. *Baseline: Only one trait is changing but the other "travels".*

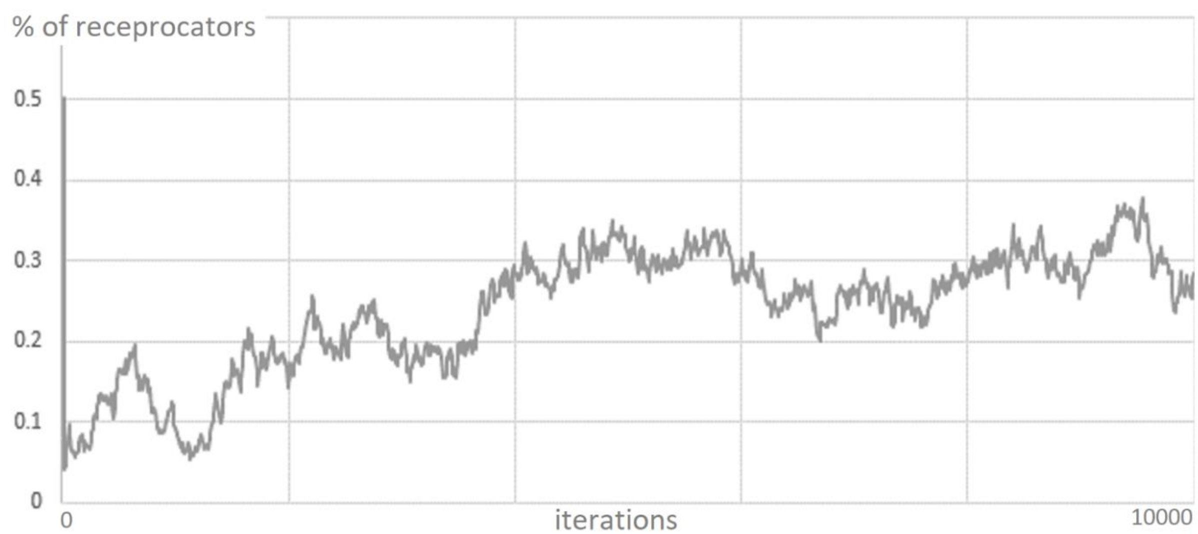
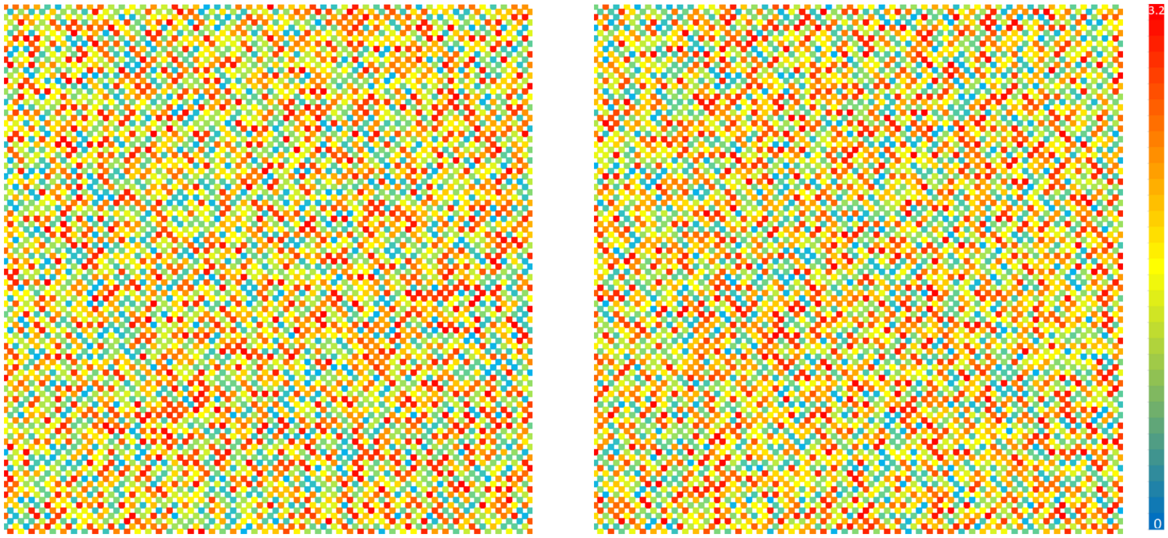


Figure 22. Average reciprocator population among type 2 agents over 10,000 iterations.

Population r value [0, 3.2]

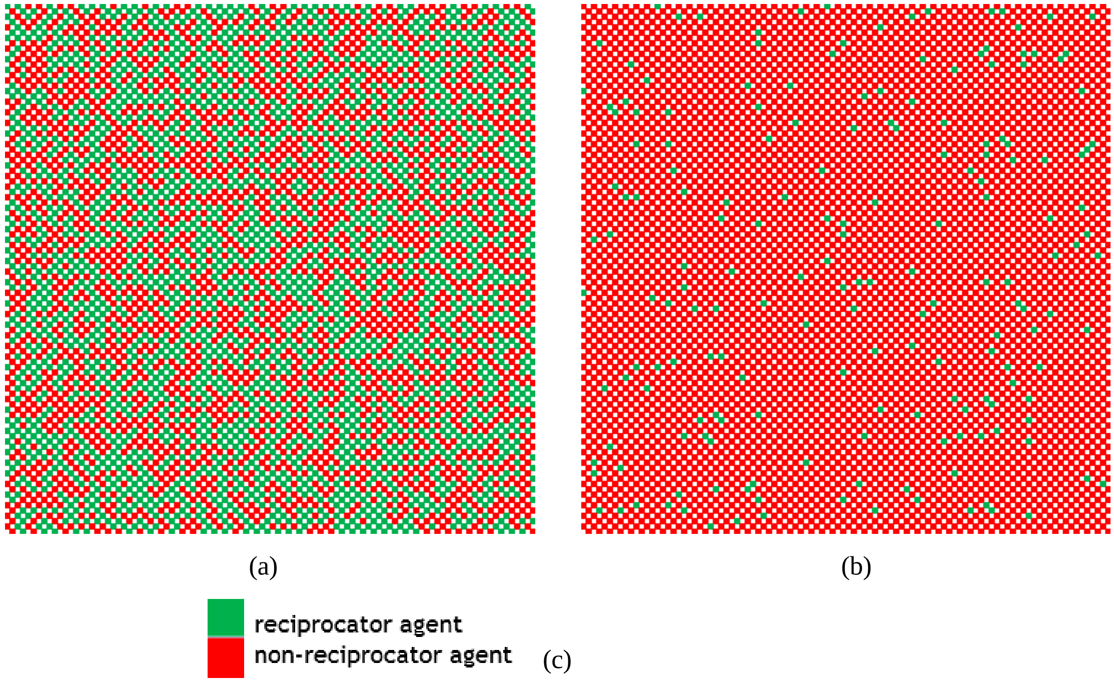


(a) (b) (c)

Figure 23. Spatial distribution of r value over type 2 agents. Initial distribution (a) on the left and final distribution (b) on the right. (c)Values closer to red are the highest, values closer to blue are the lowest.

Agents play the trust game repeatedly with their neighbours whose distance is 1. That is, the probability of being matched with another agent farther than two boxes from a Player 1's location is zero. Therefore, interaction only happens within a small area around the agents' locations. This is what we call 'local interaction'.

Starting with different spatial and behavioural distributions of type 2 agent populations, Figure 24 shows that the populations of reciprocators tend to aggregate in clusters. We start with randomly spatial distribution of type 2 agents with proportions of 1 out of 2, 1 out of 4, 1 out of 32 and 31 out of 32 reciprocator agents.



(a) (b) (c)

Figure 24. Initial populations of type 2 players. Proportion of reciprocator agents is 1/2 on the left (a) and 1/32 on the right (b). Red dots are non-reciprocators agents, green are reciprocators and whites are type 1 agents (c).

After 10000 iterations, it does not matter that what was the initial population of type 2 agents seems to aggregate in clusters of reciprocators (green) and not reciprocators (red). Figure 25 shows that clusters of reciprocators, among the populations that had different amounts of reciprocators initially, end with similar amounts of reciprocators. Meanwhile, the population of type 1 agents kept their entropy and heterogeneity (Figure 23). The amount of reciprocators among type 2 agents in these simulations ended with values from 9% to 20%, independently of the initial proportion of reciprocators.

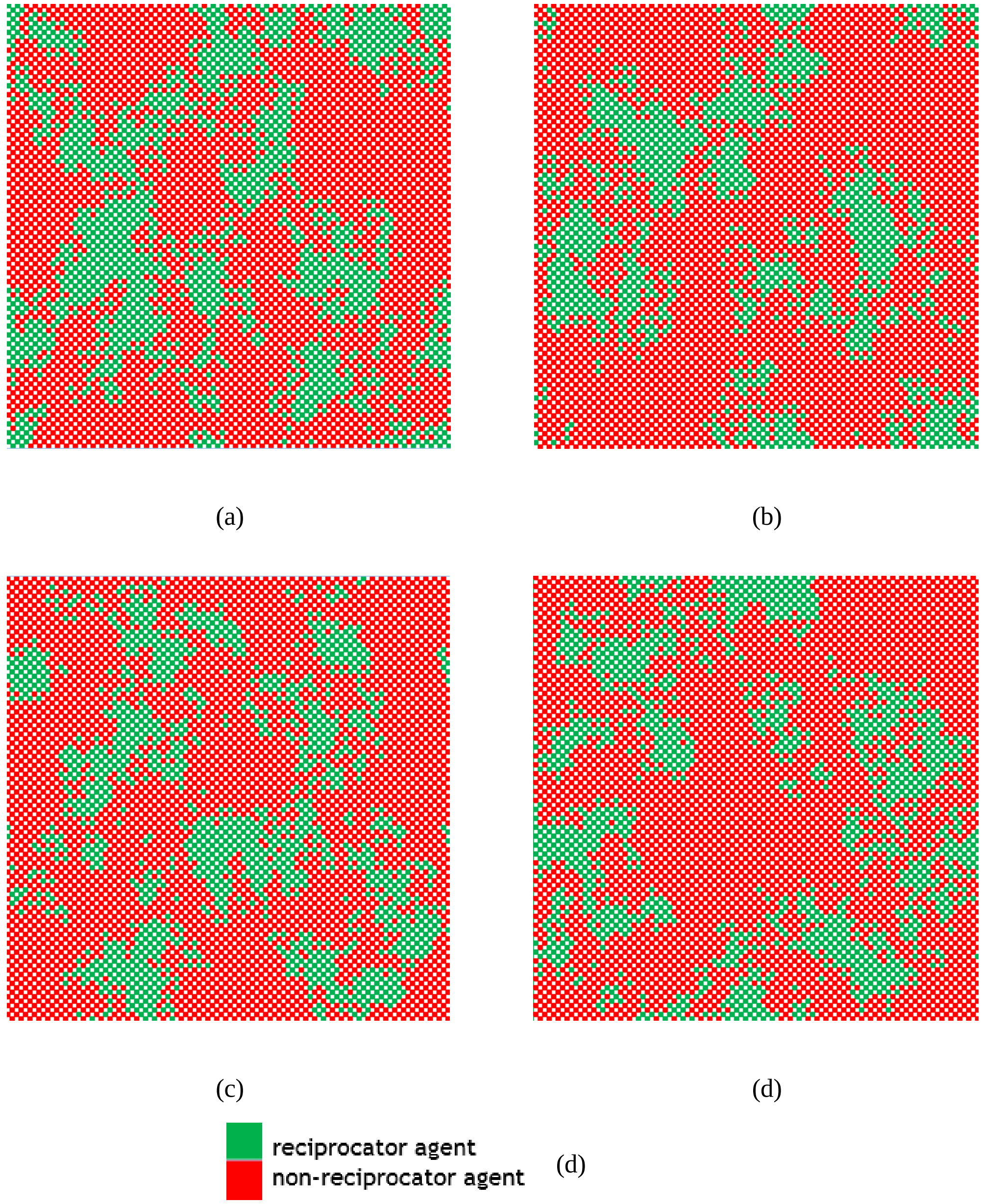


Figure 25. Final populations of type 2 agents with reciprocators initial distribution from left to right and from up to down of ½ (a), ¼ (b), 1/32 (c) and 31/32 (d) proportion of reciprocators. (d) Green dots are reciprocators and red dots non-reciprocators.

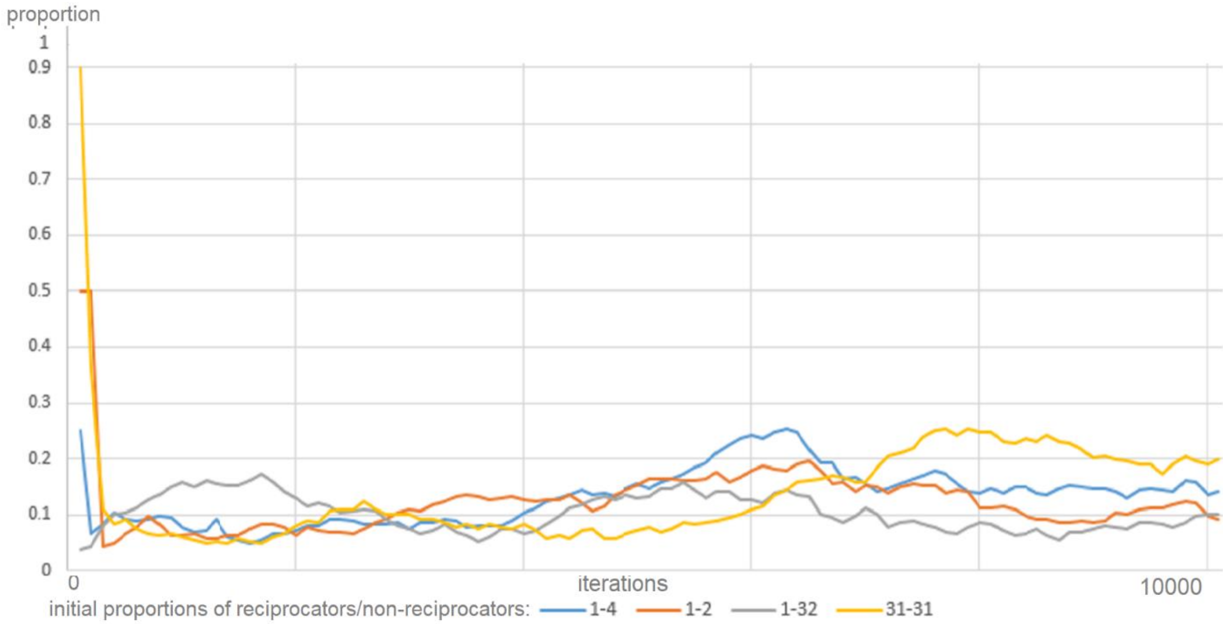
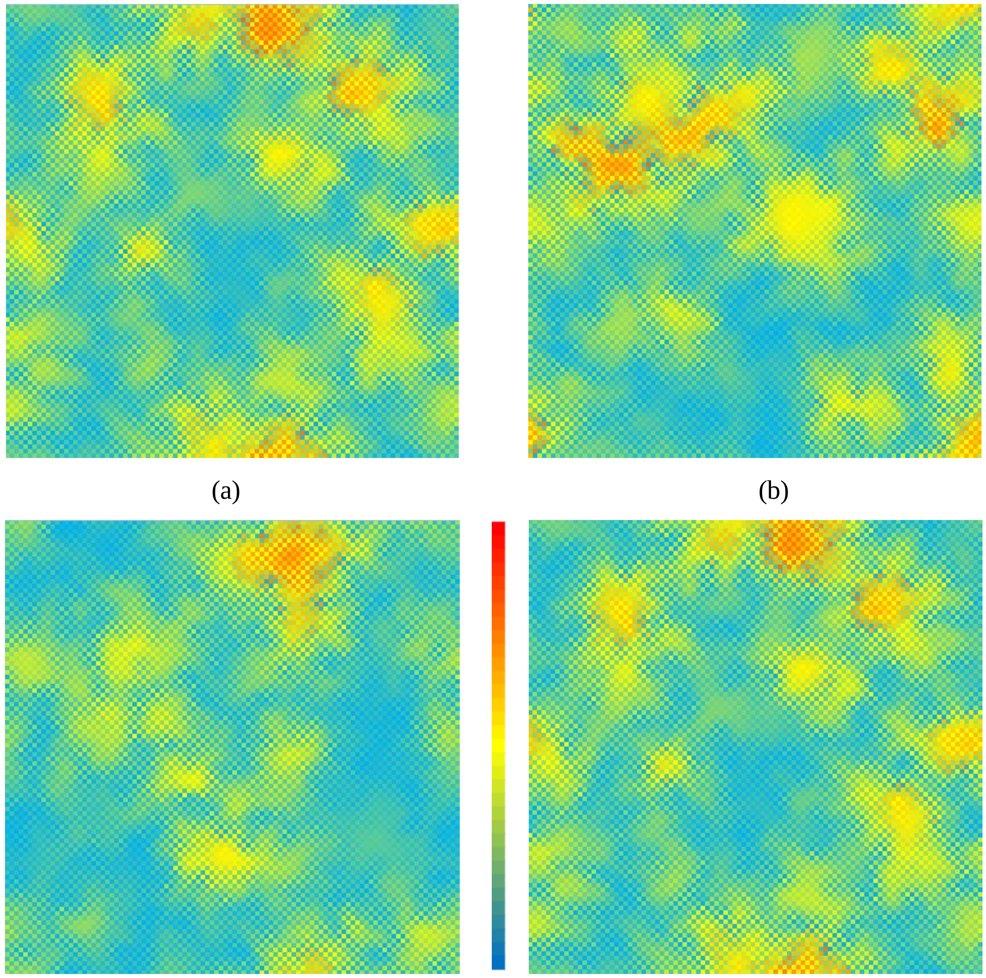


Figure 156. Reciprocator proportion in the population over 10,000 simulations starting with different initial distributions.

This aggregation is related to wealthy neighbourhoods. In Figure 27, we can recognize clusters with better performance. Namely, greater accumulated payoffs (areas in red) that correspond to the areas with higher amounts of reciprocators from Figure 25. The areas that have type 1 and type 2 agents with higher accumulated payoff are the areas that have clusters of reciprocators.

In these baseline simulations, where only the parameter of reciprocity changes over the time, all of them get the same amount of reciprocators between 9 to 20%. We can see in Figure 26 how four different simulations with four different populations evolve to these values, these populations are the same four that we can see in Figure 26 and 27.

What would happen if we change the average value of r? This is what you can find in next section.



(a) (b) (c) (d) (e)

Figure 167. (a), (b),(c), (e), Accumulated payoffs of type 1 and 2 agents after 10000 iterations. Each dot is the colour coded accumulated payoff (d) colour scale for values, red indicates high values and blue indicates low values.

4.2. Cautious societies are blessed with fewer psychopaths

We repeated the same simulations, but now the type 1 agents only have values from 1 to 2, i.e. risk-loving.

Simulations in this section explore what would happen if type 1 agents had values of r equal to or greater than 1. What happens in a society where its members are more prone to take risks when interacting with others?

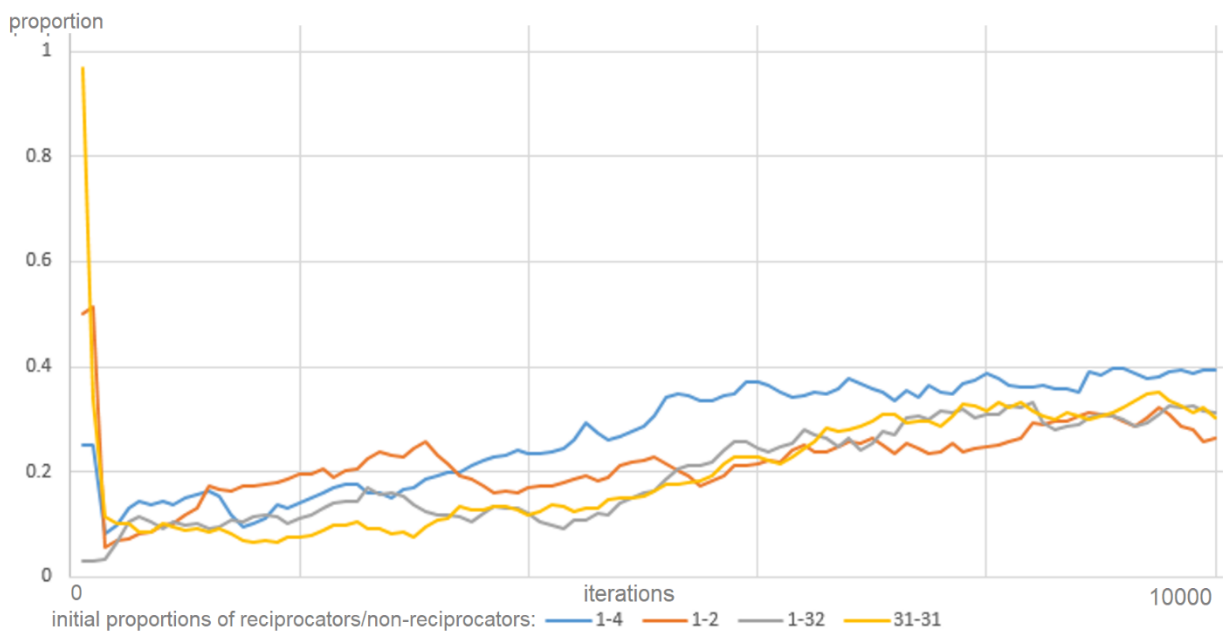


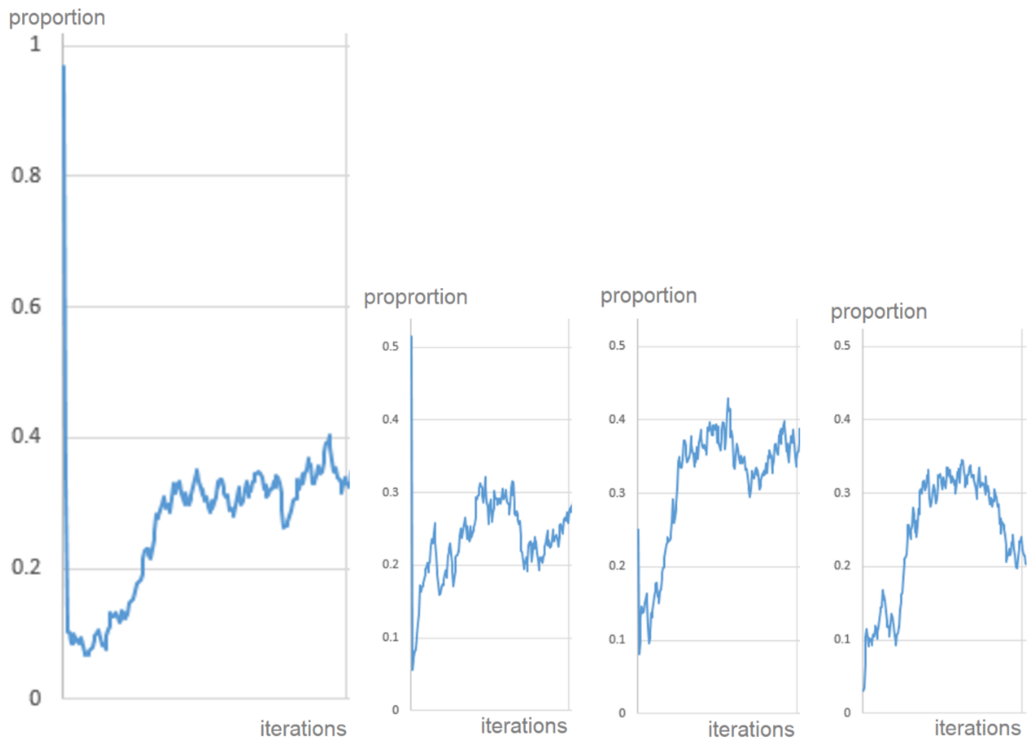
Figure 17. Evolution of reciprocator population over 10,000 generations interacting with a population of risk-lovers

This simulation replicates the previous one with four different initial populations and random spatially distributed proportions of reciprocators (1/2, 1/4, 1/32 and 31/32). Local interaction among the agents imitates the best locally updating rule for type 2 agents and the random swap of r value for type 1 agents. However, in these four different initial populations, r value for type 1 agents are the same: they have values from 0 to 1, uniformly distributed and randomly allocated in the lattice.

As we can see in Figure 24 all populations, no matter the initial conditions, the amount of reciprocators converge to a value between 0.25 and 0.4, whereas in the previous simulation with values of r between 0 and 3.2, the amounts of reciprocators converge to 0.9 and 0.2.

Notice in Figure 25, the same phenomenon occurs in the three examples with higher values of reciprocator proportions. In all cases, reciprocator population rapidly decays to percentages of 5 to 9 and then starts to rise steadyly until they achieve dynamic equilibria.

This simulations compared to the previous one in section 4.1. get larger amounts of reciprocators. However repeating the same simulation but with populations of risk neutral and risk averse player 1 agents (with r values between 0 to 1) the amount of reciprocators is bigger.



(a) (b) (c) (d)

Figure 18. Evolution of reciprocators in 2000 generations. Proportion of reciprocators: (a) 31/32, (b) 1/2, (c) 1/4/ and (d) 1/32.

Cautious subjects enhance the arising of reciprocators

After repeating the previous simulations, but with lower values of r, we found that there is an improvement in the number of reciprocators if the population of type 1 agents have r values from 0 to 1 (i.e. risk-averse and risk-neutral). All the populations in the simulations converged to 80% of the population being reciprocated (Figure 26).

This result agrees with Chapter 2 mentioned papers such as Eckel and Wilson (2004). One of the findings of their experiments is that risk-lovers reciprocate less. In the simulations with larger proportion of risk-lover agents the amoutnt of reciprocators is less. Moreover, risk-averse players reward pro-social players (Hauert 2010). This is the other interpretation we can do.

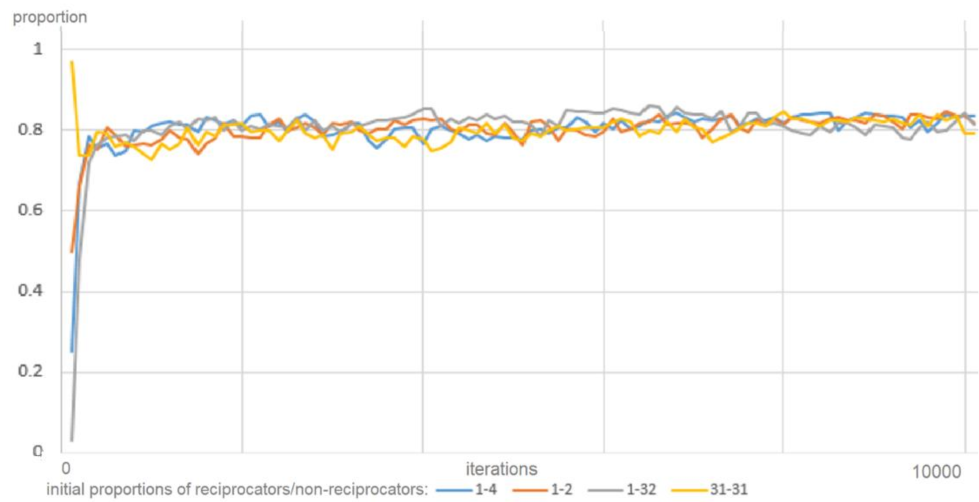


Figure 19. Proportion of reciprocators across 10,000 generations interacting with risk-averse agents.

4.3. Without changes in reciprocator population, risk aversion does not evolve

Letting the type 1 agents evolve but then keeping the reciprocator population fixed produces no changes in the population of type 1 agents. Figure 27 shows the average value of the r parameter of all type 1 agents in six independent simulations with the same initial populations. Interaction is local and type 1 agents after each generation perform ‘local imitate the best’. Meanwhile, type 2 agents do not change their strategy. We can see the population of type 2 agents in Figure 29 (b). The population of type 1 agents have uniformly distributed r values (from 0 to 1) and are spatially arranged in order to minimise the differences between neighbours Figure 29. After running six simulations with four different populations of reciprocators (1/32, 1/4, 1/2 and 31/32), the outcomes are the same, the values of r change very little and initial and final populations after 10,000 generations are indistinguishable Figure 28. Notice the values of r in the y axis change less than 0.001.

This simulation is a good example in order to defend this research because the changes in the population are more close to reality when instead of changing only one parameter the co-evolution is allowed.

Trying to keep the ceteris paribus criteria we might lose emergences in the population or realism. This is one more reason to defend simulations, in order to study parallel complex events (Gilbert and Troitzsch 2005,Gilbert and Troitzsch 2005) with simple rules (Kirman 1993; Axelrod 1997) as we read in section 2.4.

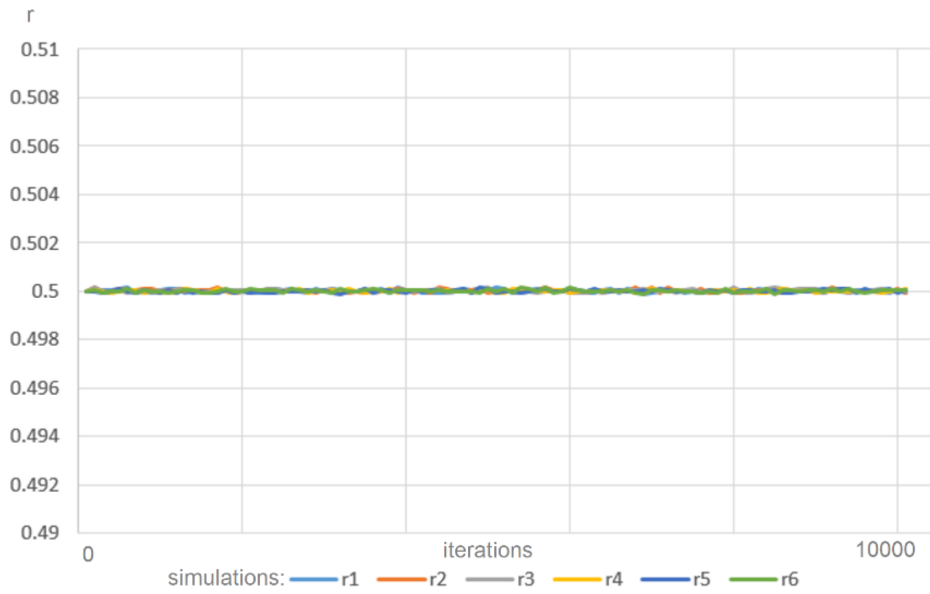
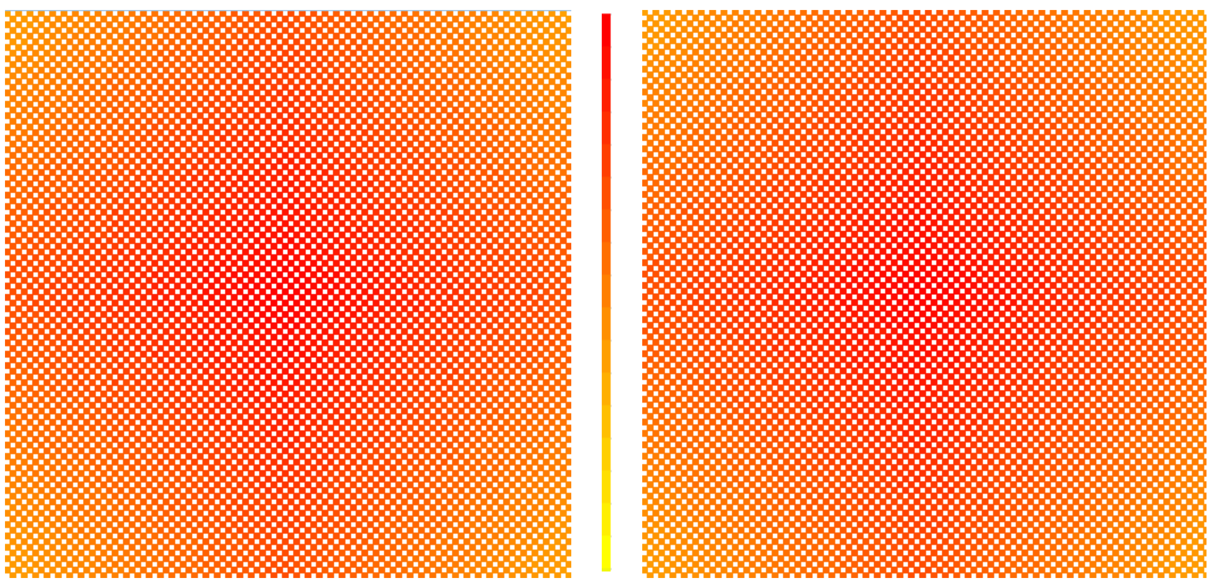


Figure 20. Evolution of r average value in six different populations during 10,000 generations



(a) *(c)* *(b)*

Figure 21. Distribution of the parameter r over the lattice. Initial on the left (a) and final on the right (b) after 10,000 iterations. Value of r is 0 in the centre and 1 in the corners.(c) 0=yellow, red=1.

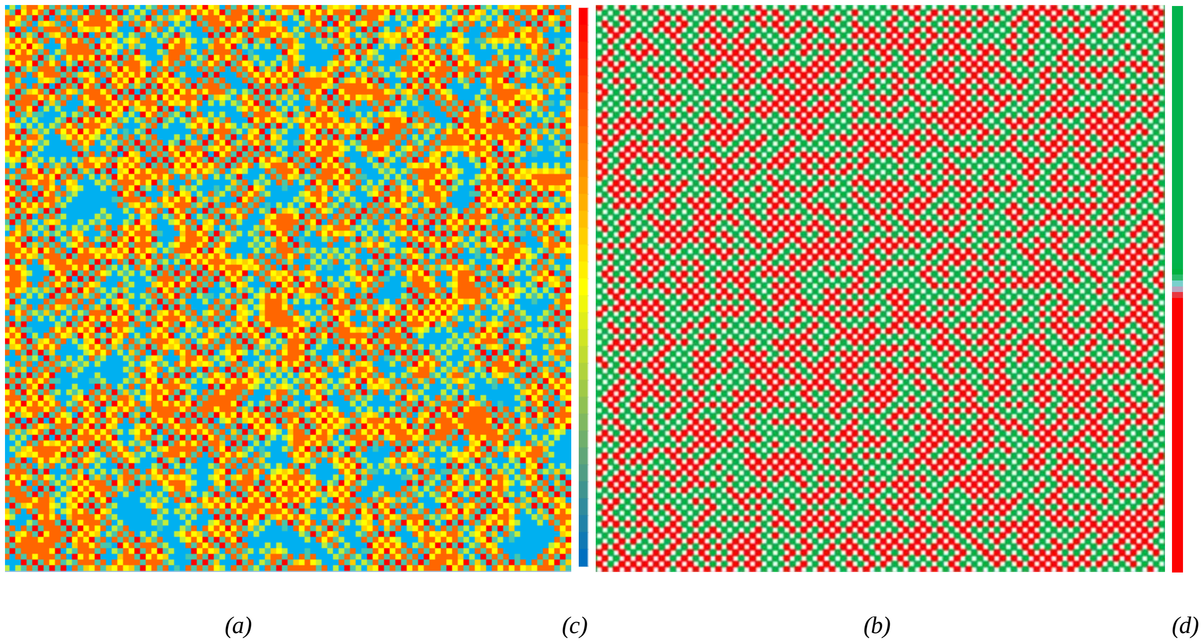


Figure 22. (a) Accumulated payoff of the agents (type 1 and 2) on the left, red colour cells are the agents with higher accumulated payoff. (b) Population of type 2 agents.(d) Green is a reciprocator agent and red is a non-reciprocator agent.(c)blue is the lower value for payoffs and red the maximum.

4.4. Coevolution and why some societies have more difficulties improving their trust

What happens when two different countries adopt the same strategy? Why some of them success and others do not success? We repeated the same simulations with local imitation and interaction, but this time both agents evolved. In these circumstances, the speed of evolution of type 2 agents converges to final populations faster than type 1 agents. The type 1 agents' average value for r do not change much as we can see in Figure 31. This difference drives to local ESS. Simulations with four different populations were executed and populations of type 2 agents converged too quickly to ESS. Type 2 agents evolved to two populations, one with all type 2 agents reciprocating and the other one with half of them reciprocating Figure 32. Depending on the initial proportion of reciprocators among them, populations are deemed to have more or less reciprocators. However, the populations of type 1 agents do not evolve in their average value of r, as mentioned above, and the spatial distribution has no order Figure 33.

Initial proportions of type 2 agents determine their final populations and the accumulated payoffs of all the agents. The bigger the initial number of reciprocators, the bigger the accumulated payoff of all the population Figure 34. The way type 2 agents are ordered and payoffs are graphed reminds us to Nowak and May (1992) simulations.

In these simulations, the past matters and societies have difficulties getting out of their local equilibria. In societies with bad historical trust records, the trust confidence problem is chronic and the accumulated payoff of the agents is worse than in societies with more initial reciprocators.

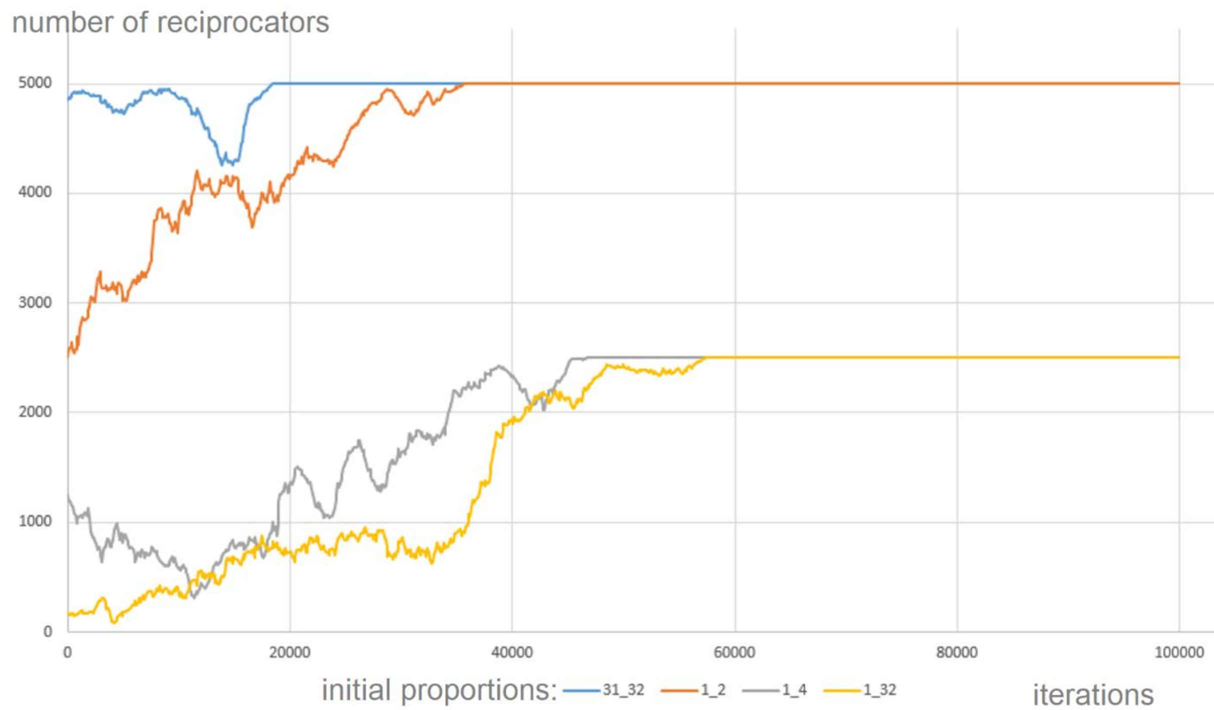


Figure 23. Reciprocator population evolution starting from four different initial distributions.

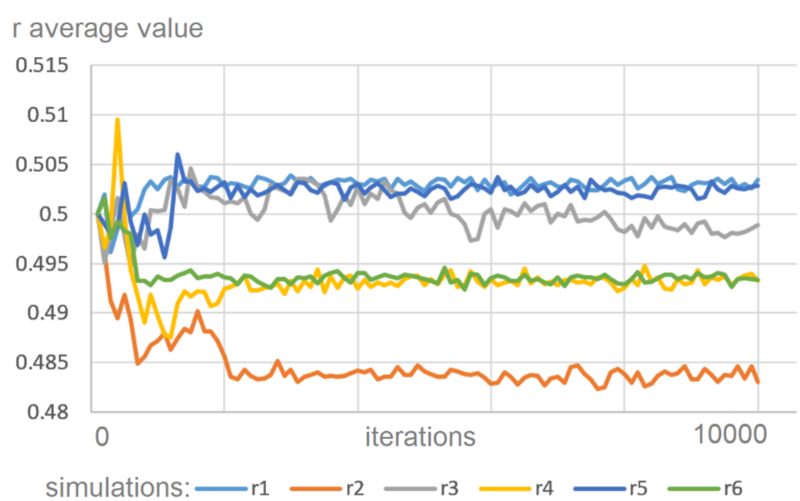


Figure 24. Evolution of r average value in six different simulations with the same initial population with a proportion of one reciprocator out of 32 type 2 agents and an average r value of 0.5

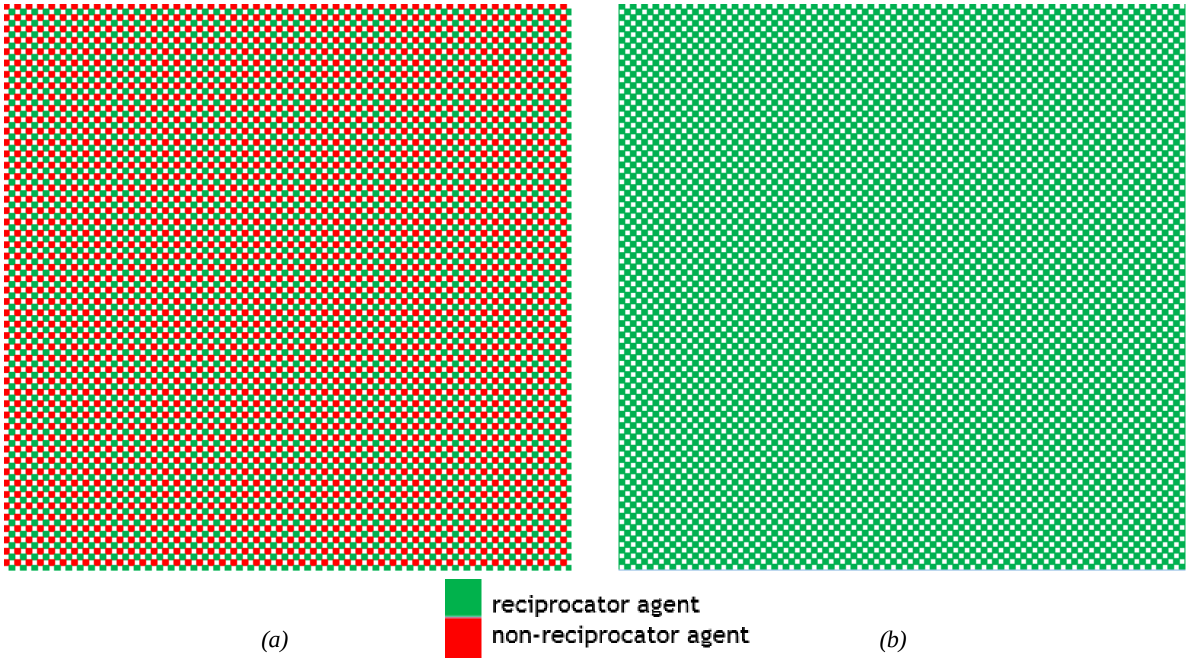
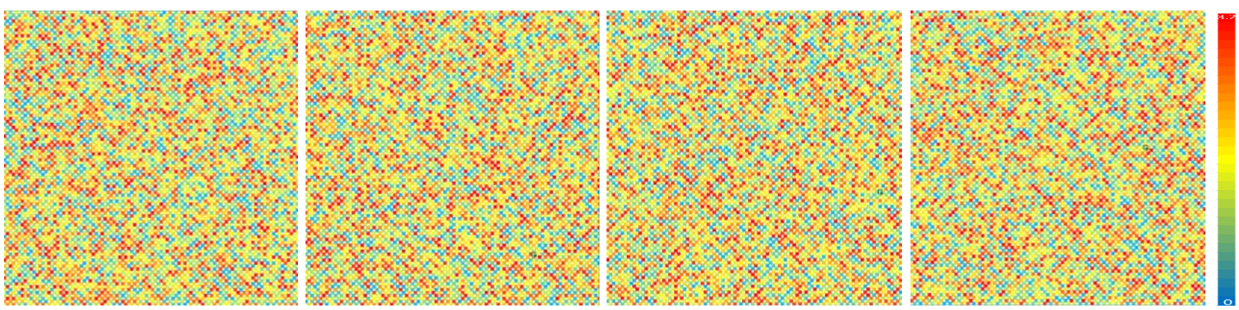
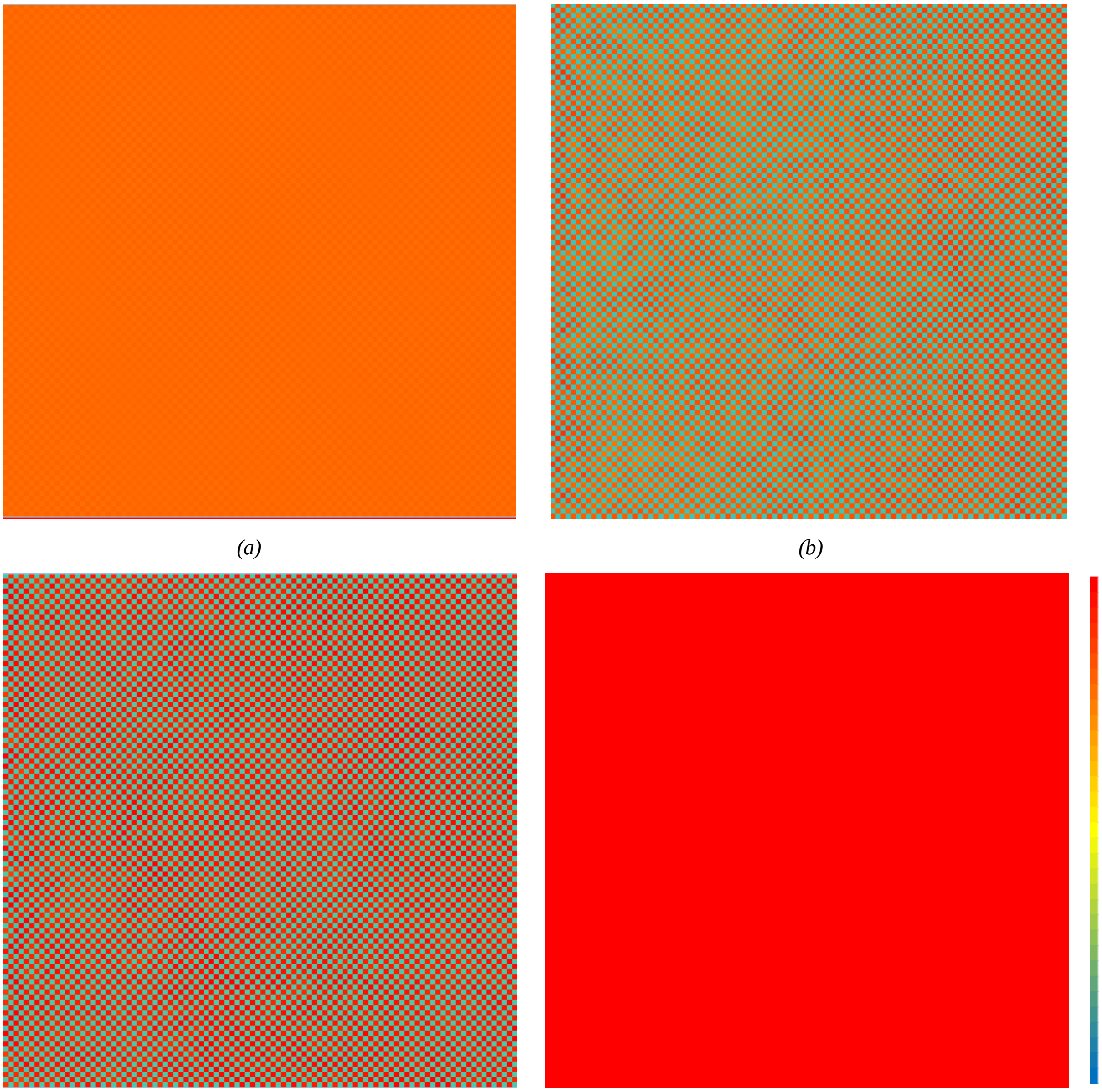


Figure 25. Populations of reciprocators. (a) Starting with 1/32 and 1/4 proportion of reciprocators. (b) With initial population of reciprocators 31/32 and 1/2 over the whole population of type 2 agents.



(a) (b) (c) (d) (e)

Figure 26. Value of r in populations of type 1 agents after 10,000 generations. Initial populations proportion of reciprocators is: (a) 1/2, (b) 1/4, (c) 1/31 and (d) 31/32 from left to right.(e) r values from 0 (blue) to 3.2 (red).



(a) *(b)*

(c) *(d)* *(e)*

Figure 27. Accumulated payoffs of the agents after 10,000 generations depending on initial populations with coevolution of both agents. Proportions of reciprocators are (a)1/32 (b)1/4 (c)1/2 and (d)31/32. (e)Values closer to red are the highest accumulated payoffs and closer to blue are the lowest accumulated payoffs.

4.5. Sucessful strategies do not have to be suitable for other environments

When agents interact locally but their strategies are the outcome of a random global imitation populations, they are driven to ESS with low payoffs. Type 2 agents who were lucky and interacted with reciprocators are the ones who got better payoffs because the risk-loving behaviour rises and type 1 agents are incentivized to use the ‘not reciprocate’ strategy.

Simulations were executed six times with four different populations for 10,000 generations. The populations were randomly spatially distributed with proportions of reciprocators of 31/32, 1/4, 1/2 and 1/32; r value is uniform between 0 and 3.2.In all cases, the r value, on average, evolved to risk-loving and the number of reciprocators disappeared even when the initial populations of reciprocators was very low (1/32), as we can appreciate in Figure 35 and Figure 36.

These simulations might be fine-tuned selecting the distance of one agent to another. Measuring the similarity of one agent as the difference of their parameters we can imagine that agents that are more similar would be more prone to copy strategies if they are successful. Including this idea would make evolution slower and “Armageddon” events (all the population not reciprocating) would happen less.

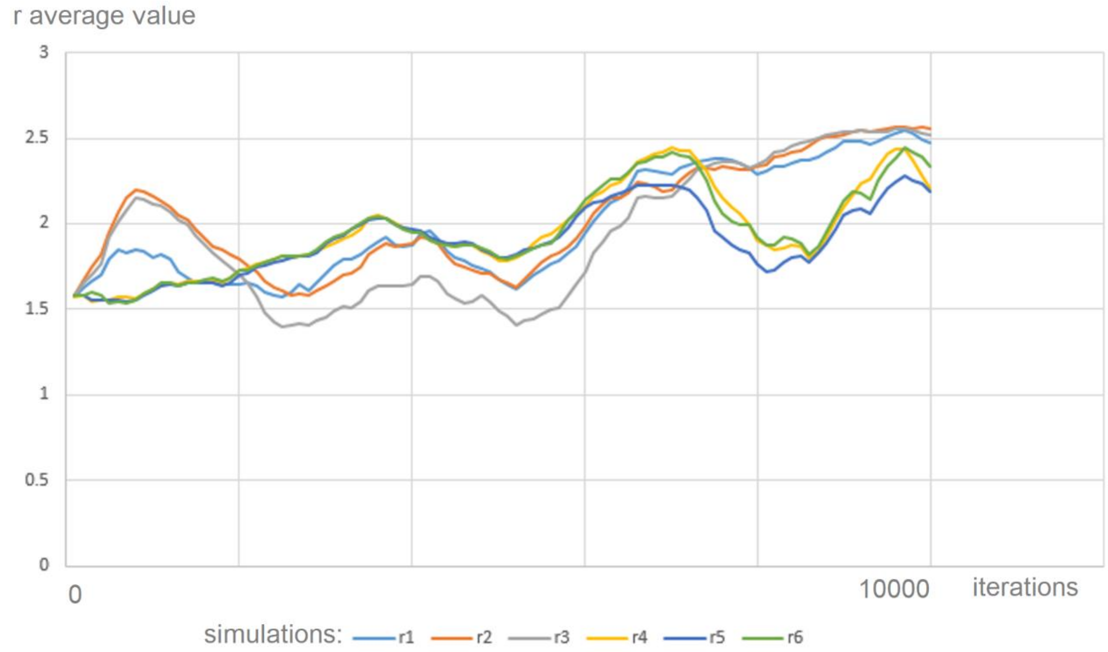


Figure 28. Evolution of the average value of r in six simulations of 10,000 generations.

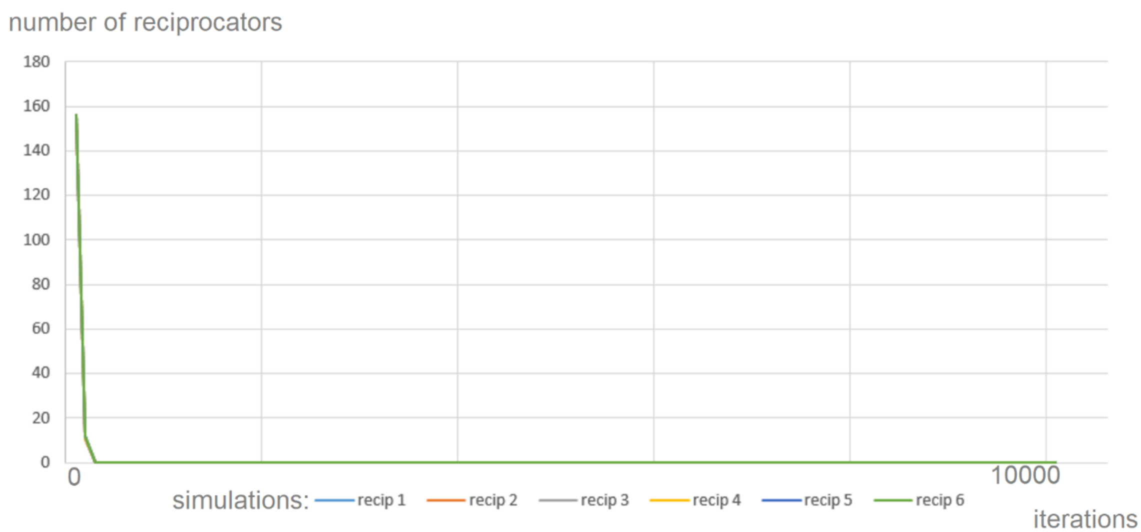


Figure 29. Reciprocator evolution over 10,000 generations. Total population of type 2 agents is 5000.

4.6. Even with risk-averse and risk-neutral agents, civilizations do not improve

Another way to avoid too optimistic agents emerging is to start the simulations with more averse populations. We repeated the simulation of the previous section, but instead of having r values from 0 to 3.2, type 1 agents had r values from 0 to 1 (risk-averse and risk-neutral). Simulations were executed six times with four different populations for 10,000 generations. The populations were randomly spatially distributed with proportions of reciprocators of 31/32, 1/4, 1/2 and 1/32.

Even with 50% of the initial population of type 2 agents reciprocating in all their interactions, the simulations ended up with reciprocators becoming extinct; meanwhile, the average r values were unpredictable. In this situation the agents type 1 are not becoming risk lovers.

Figure 30. Evolution of the average value of r in six simulations with the same initial population

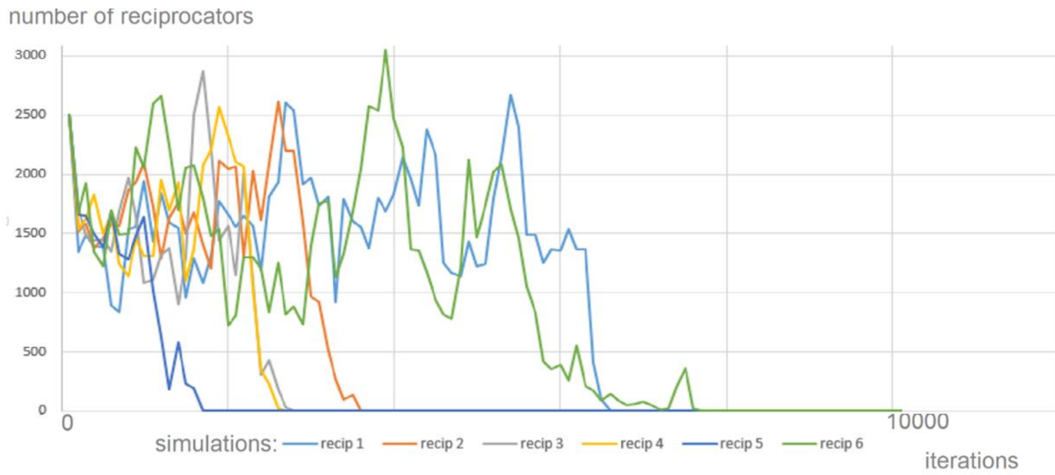


Figure 31. Number of reciprocators out of 5000 agents over 10,000 generations in six simulations.

4.7. Getting out of local equilibria: mutations

Mutations can be employed to maintain heterogeneity and move the system out of weak local ESS. Figure 32 shows the results of simulations with the same initial populations and parameters, but with mutations. In previous sections, in many cases, simulations ended with the extinction of the reciprocator agents. However, if the heterogeneity is preserved with mutations it is less likely that these populations of reciprocators disappear. Thanks to these mutations populations of type 1 agents end clustered with other agents with closer values of r while something similar happens to type 2 agents. Moreover, there are clusters of both type agents who get the same accumulated payoff (third column). In the areas with better performance both agents get the same accumulated payoffs but in the other areas there is inequality between agents.

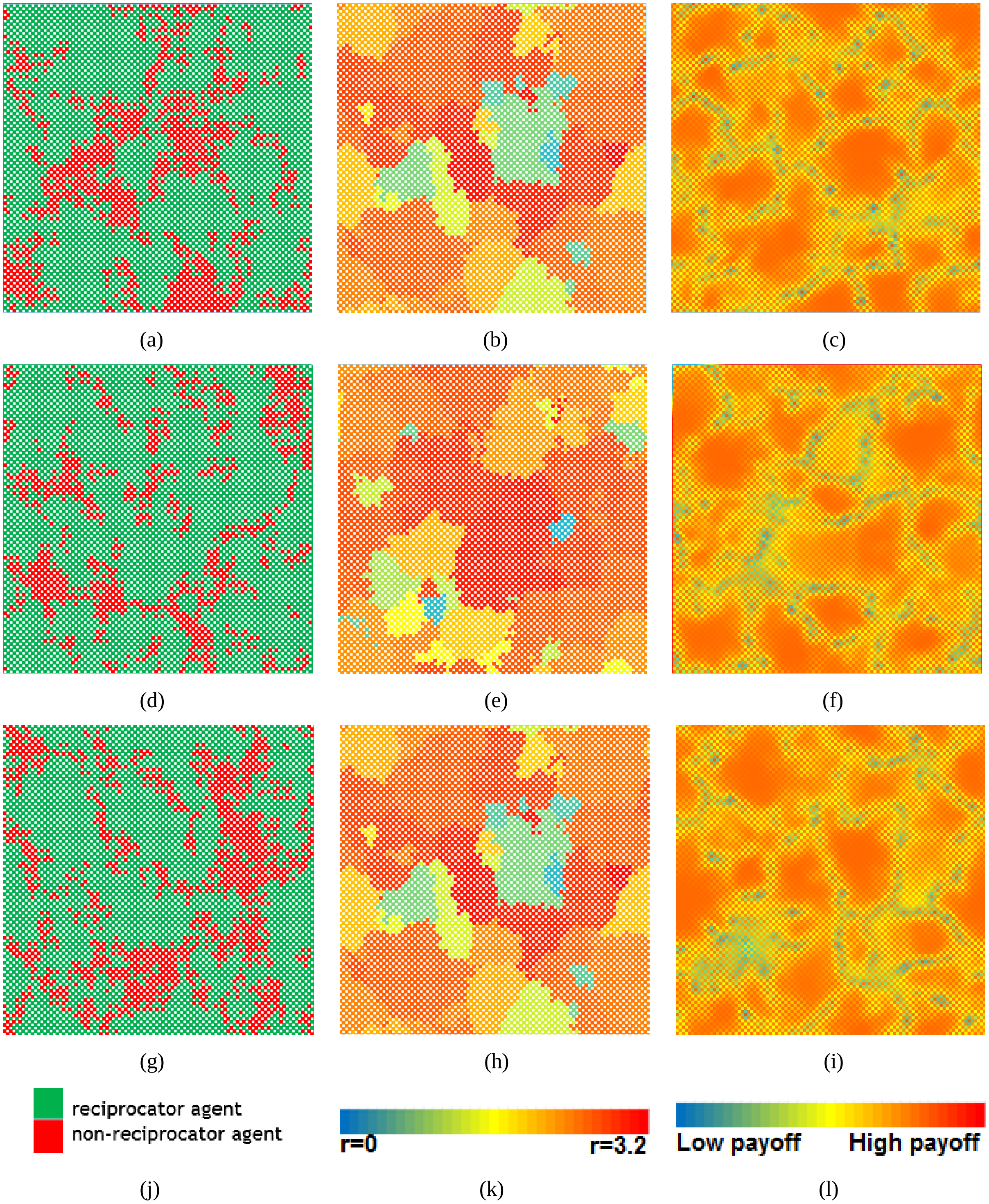
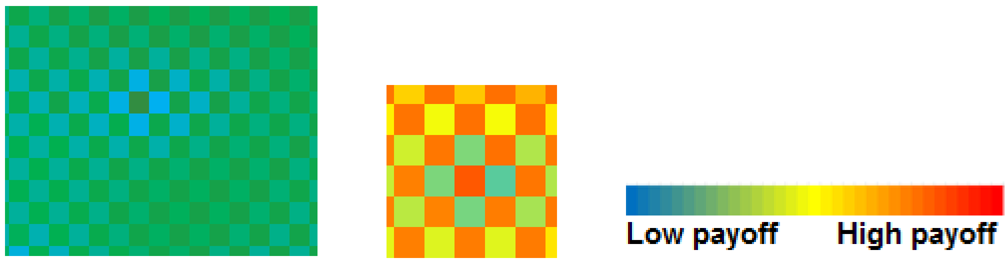


Figure 32. Results after 10,000 generations. From left to right, (a), (d), (g) values of type 2 agents, (j) green agents are reciprocators and red agents non-reciprocators. (b), (e), (h) r values of type 1 agents (k) blue values are 0 and red are 3.2 ;and (c), (f), (i) accumulated payoffs, (l) red colour are the higher accumulated payoffs.

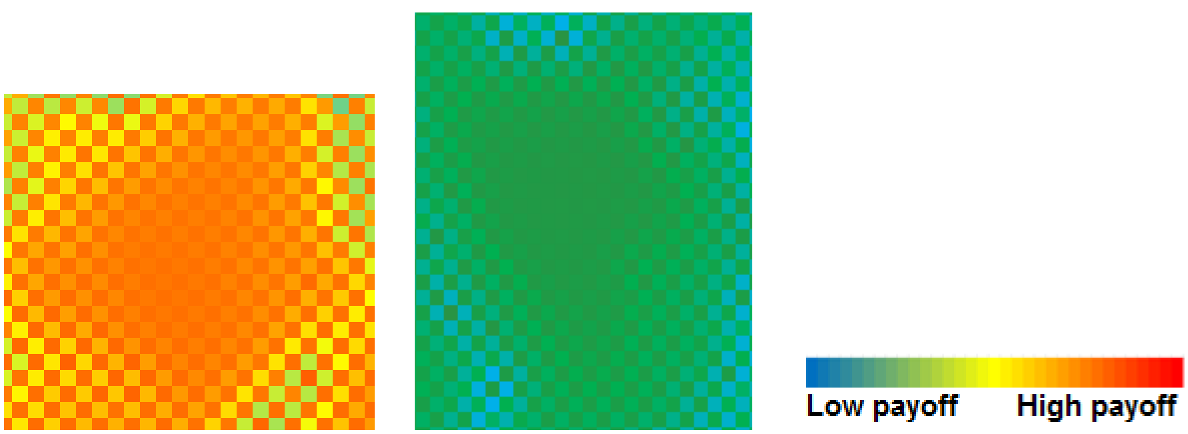
We can appreciate where psychopaths affect their environment in Figure 33. Green is more money than blue and red more money than blue. The central agents of this images are psychopaths that take advantage of their neighbours as mentioned in section 2.6 (Frank 1988; Mealey 1995; Murphy 2006; Sachs and Simms 2006; Glenn et al. 2011).



(a) (b) (c)

Figure 33. Accumulated payoffs detail. (a), (b) surrounding area close to psychopath. The psychopath has higher accumulated payoff and its neighbours are affected negatively. (c) Colour interpretation.

Reciprocators and risk-lovers have a fruitful outcome (Figure 34). However, psychopaths have better performance in difficult environments (Taylor and Armor 1996).



(a) (b) (c)

Figure 34. (a) Payoffs in a risk-lover/reciprocator environment. (b) Payoffs in a risk averse/psychopathic environment. (c) Colour interpretation.

Here, the average value of r behaves as a dumped oscillator function over time and populations keep adapting to changes and possible shocks (Figure 35). Populations of type 1 agents and type 2 agents co-evolve and regulate each other.

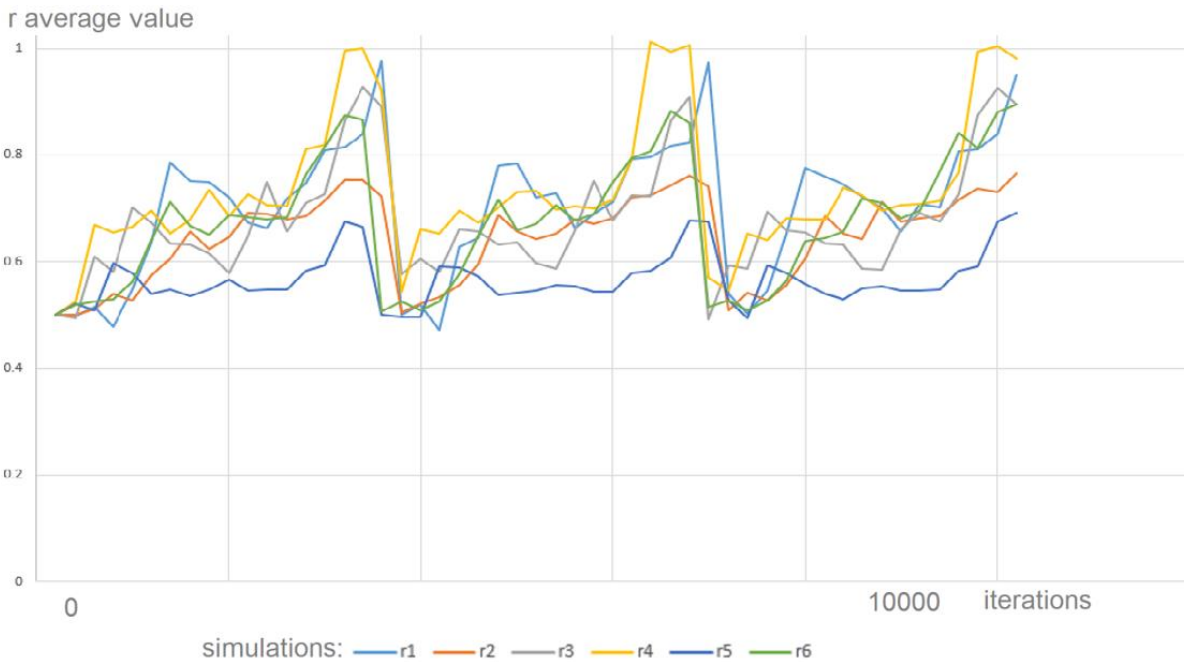


Figure 35. Average value of r over time with mutations

4.8. Global imitation and mutation

With global imitation, the system is over-dumped and oscillates too much (Figure 36). This can be modulated to medium neighbourhoods with a lower rate of mutation or imitation rules. Global imitation did not produce interesting ESS and neither does it even with mutations.

Again, with values of r from 0 to 3.2 type 1 agents tend to follow the most successful members of the society. However, this does not get the best accumulated payoffs and produce a population of type 2 agents that follow what is the "fashion" strategy. This is what would happen if all the members of the society wanted to follow their dreams as successful people do like Steve Jobs, Elon Musk, Obama, Donald Trump, Tom Cruise, etc.

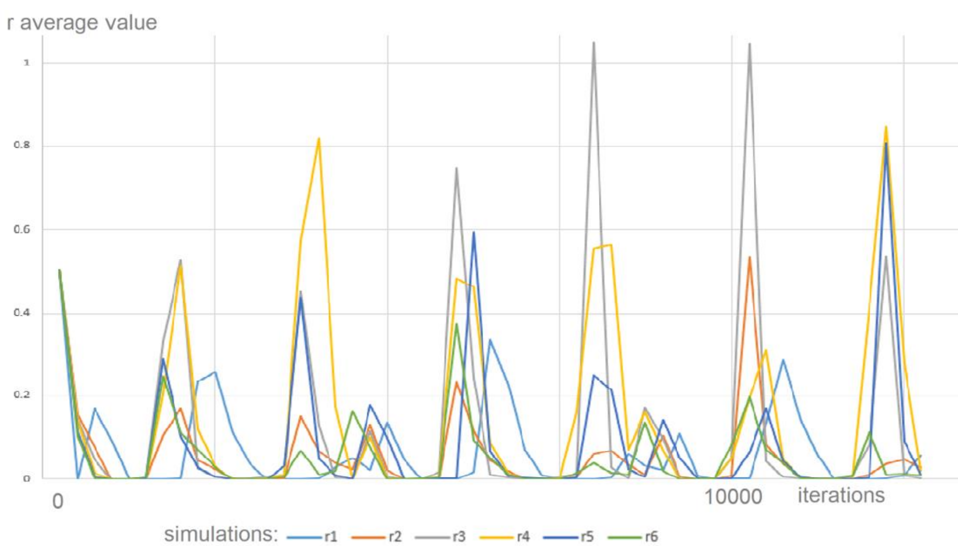


Figure 36. Over-dumped average r value in simulations with global imitation and mutations

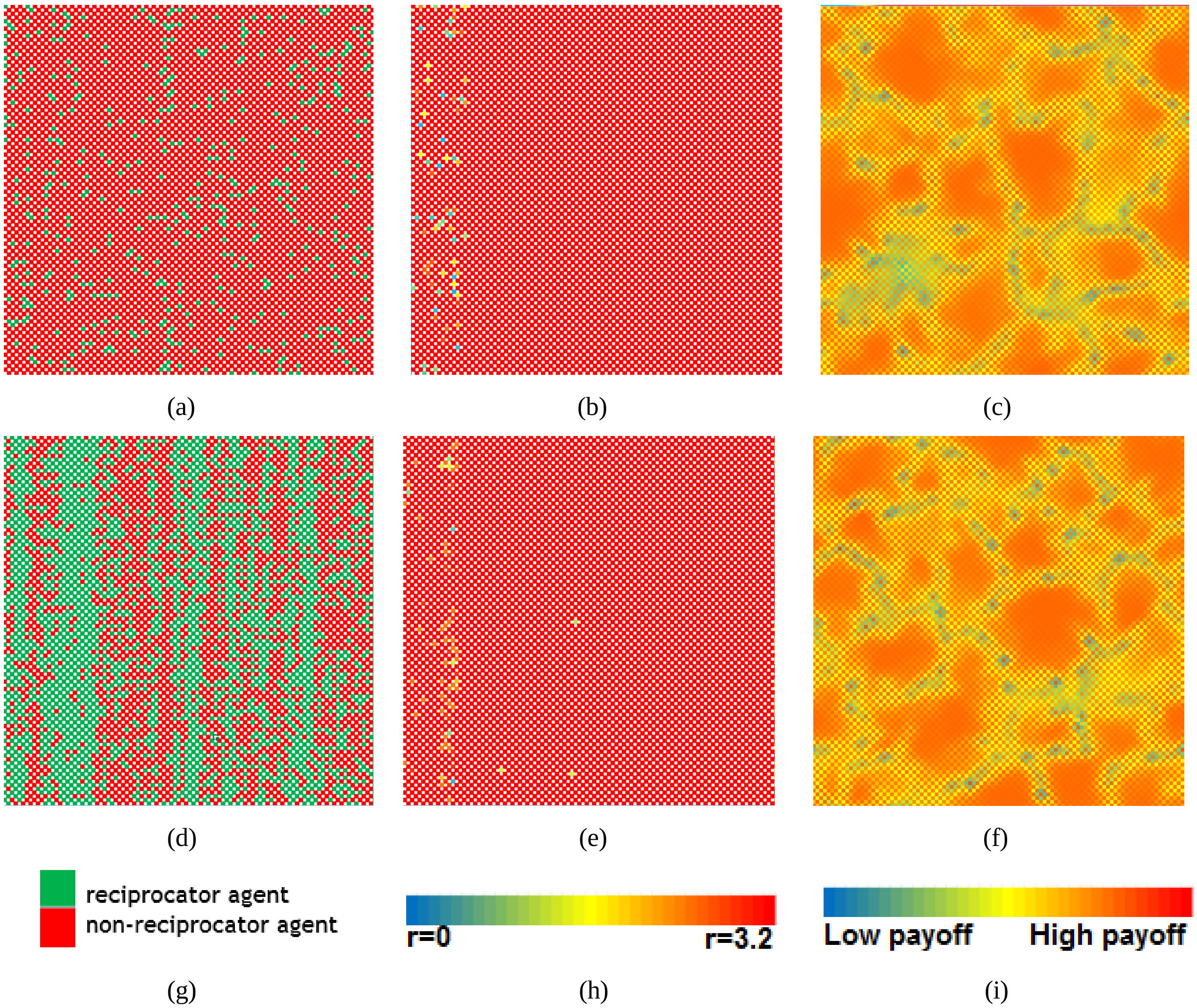


Figure 37. Different simulations with the same initial conditions. (a), (d) end populations of type 1 agents. (b), (e) end populations of type 2 agents. (c), (f) accumulated payoffs of all the agents. (g) Green dots are reciprocators and red dots are non-reciprocators (h) colour values for r (i) red colour are the highest accumulated payoffs and blue the lowest ones.

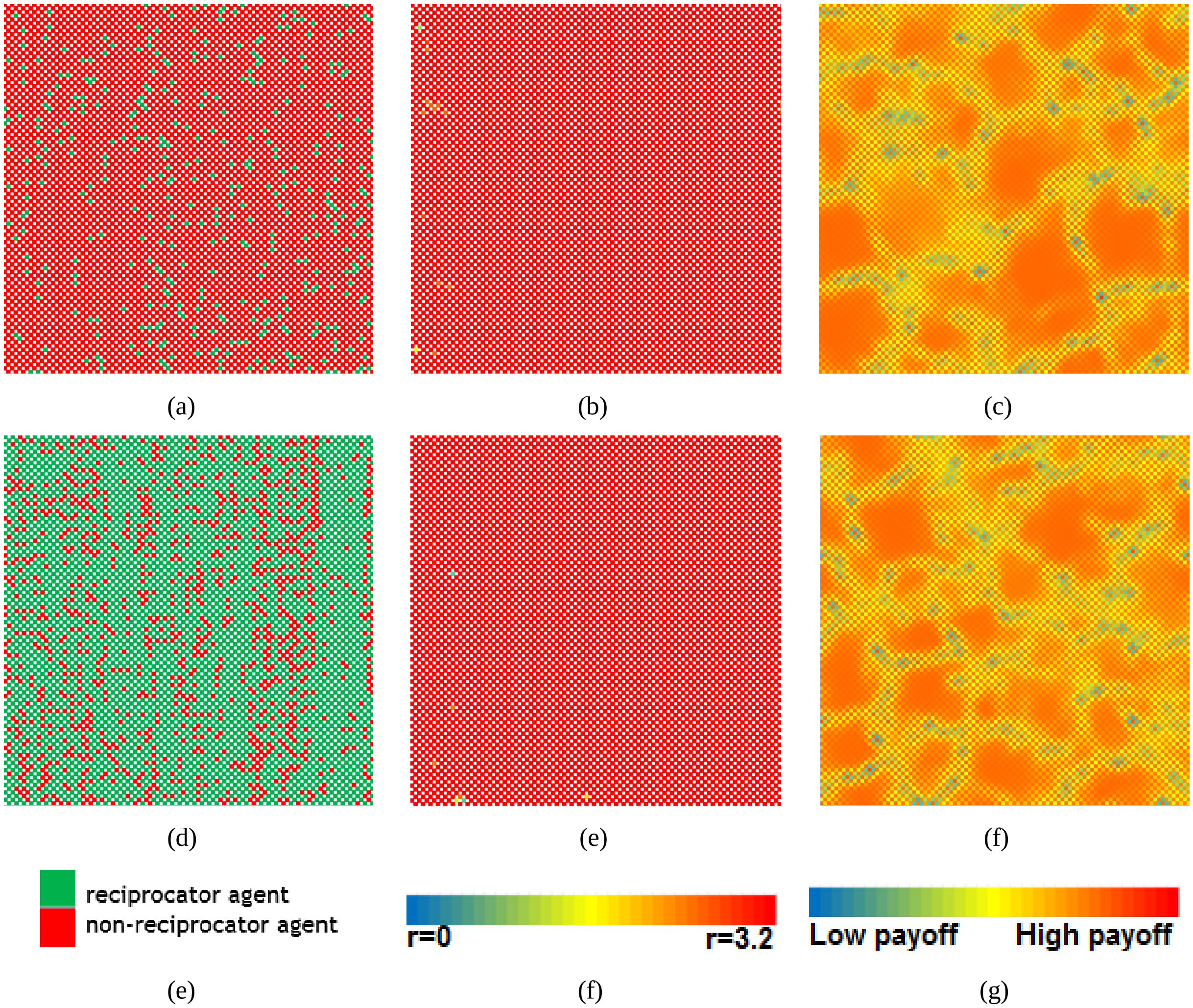


Figure 38. Different simulations with the same initial conditions. (a), (d) end populations of type 1 agents. (b), (e) end populations of type 2 agents. (c), (f) accumulated payoffs of all the agents. (g) Green dots are reciprocators and red dots are non-reciprocators (h) colour values for r (i) red colour are the highest accumulated payoffs and blue the lowest ones.

4.9. What happens if a society is already risk-averse?

This last simulation keeps the same rules, but the initial populations have values of r from 0 to 1. When a mutation happens, the value of r can be up to 3.2. This mutations can help to protect the populations in case of shocks as mentioned in section 3.3.7.

Just letting the populations start from lower values of 9r produces a system closer to reality where the reciprocators (Figure 39) and trustors evolve together (Figure 40).

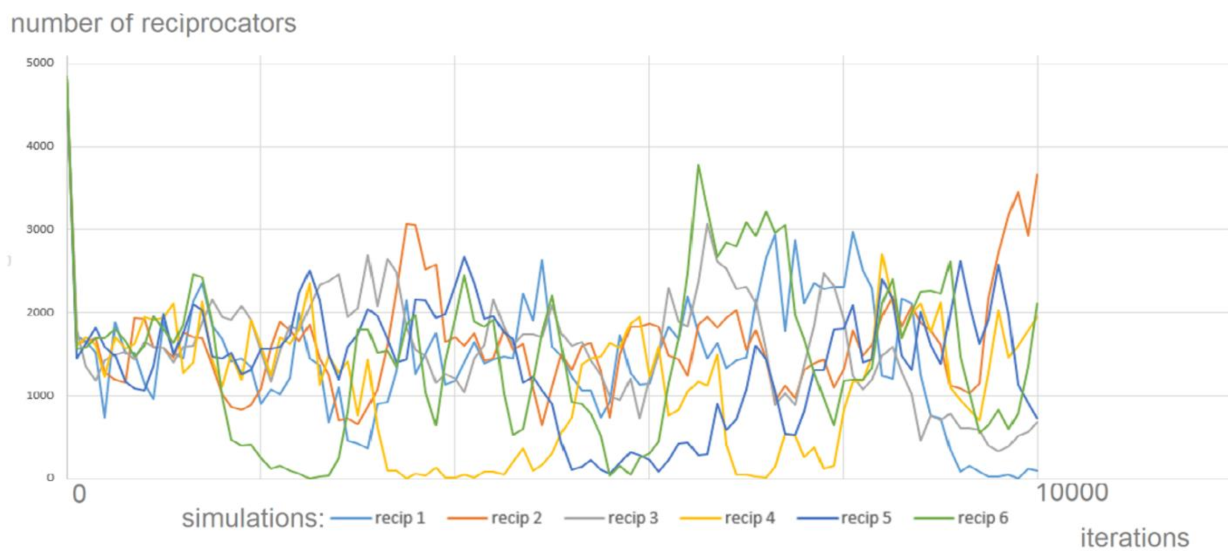


Figure 39. Reciprocator population with mutations and global imitation

Evolution of average r value over the time in six different simulations starting with the same population is chaotic but do not have tendency to go to risk averse preferences (Figure 40).

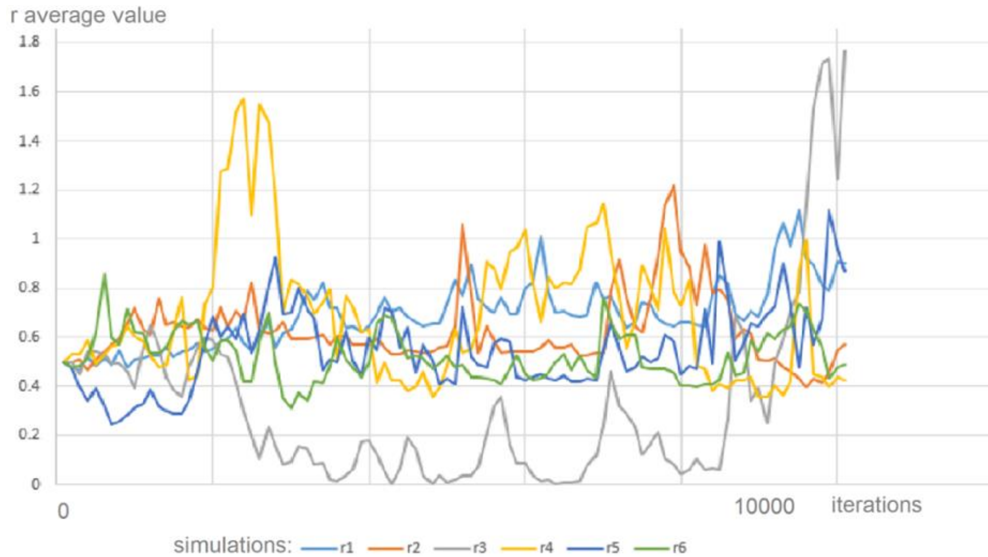
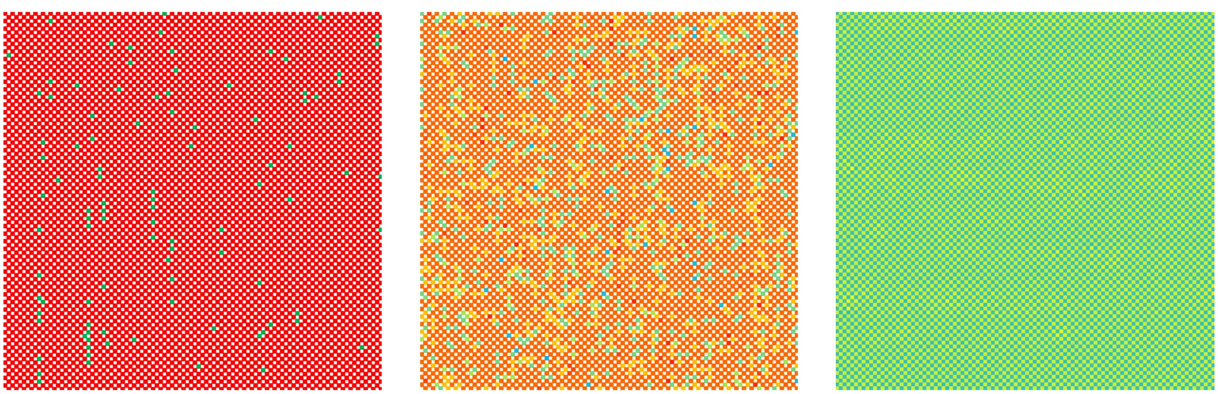


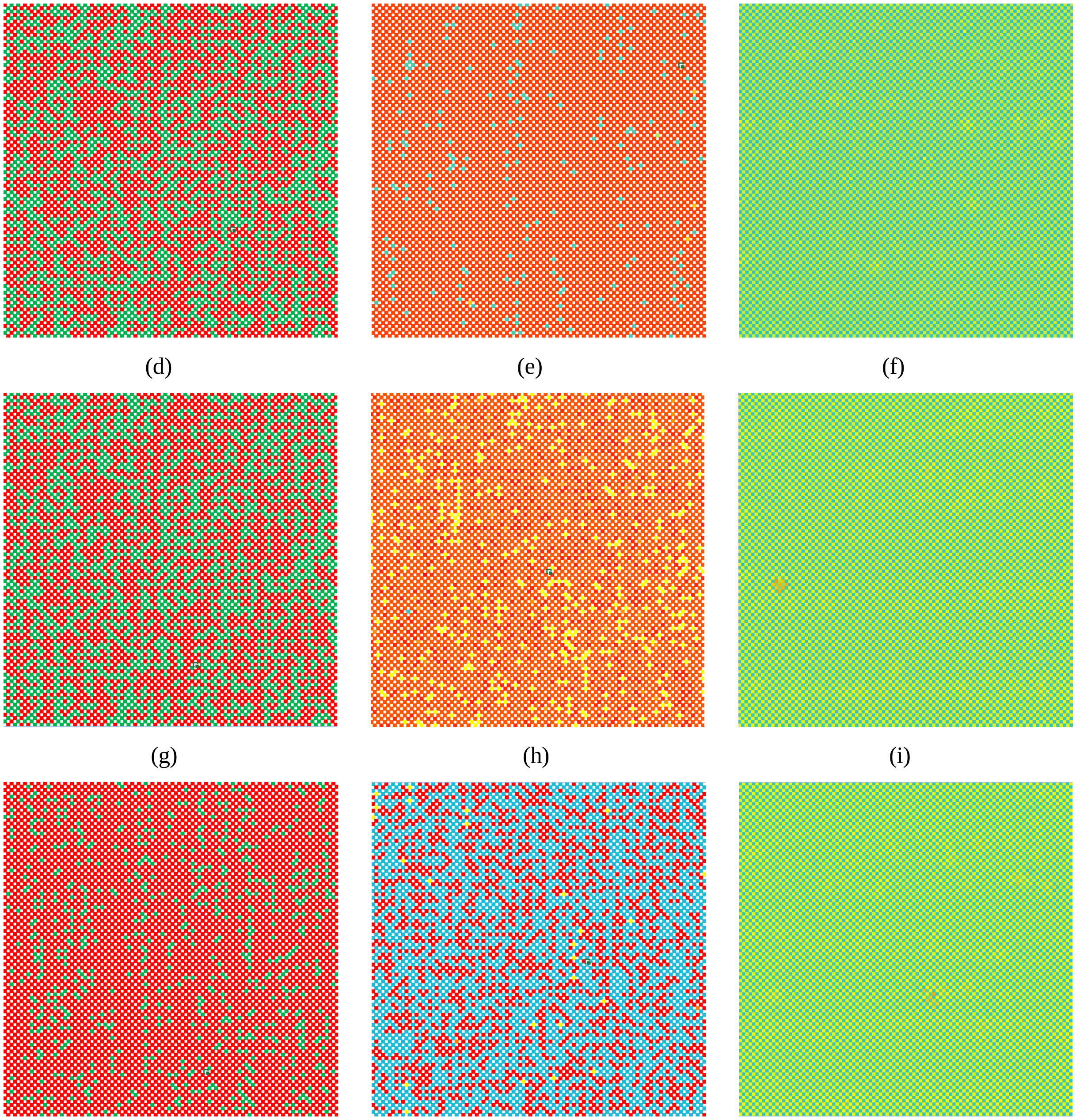
Figure 40. Average r value with mutations and global imitation.

As we can see from Figure 41, the values of r are unpredictable, but the payoffs outcome is bad.

This simulation can explain why markets with too much volatility generate less accumulated payoffs.



(a) (b) (c)



(d) (e) (f)

(g) (h) (i)

(j) (l) (l)

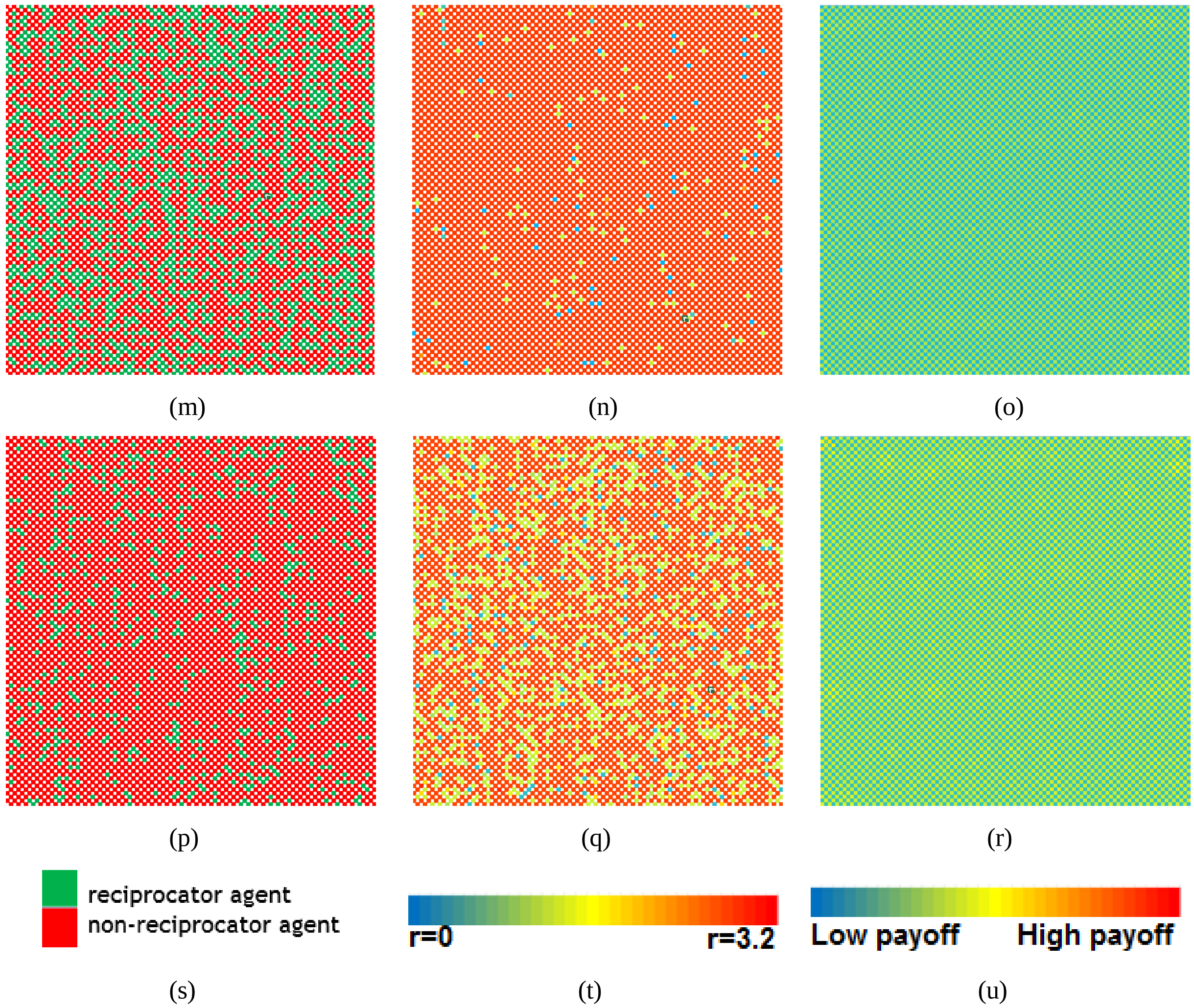


Figure 41. Different simulations with the same initial conditions. . (a), (d), (g), (j), (m), (p) end populations of type 1 agents. (b), (e), (h), (l), (n), (q) end populations of type 2 agents. (c), (f), (i), (l), (o), (r) accumulated payoffs of all the agents. (s) Green dots are reciprocators and red dots are non-reciprocators (t) colour values for r (u) red colour are the highest accumulated payoffs and blue the lowest ones.

CHAPTER 5. CONCLUSIONS

This dissertation explores the domain of ABM simulations. The aim of this research is to explore the evolutionary mechanisms for the emergence of prosocial/antisocial behaviour and to study how risk attitudes and trustworthiness coevolve parallel to each other.

Chapter 2 introduces all the literature review. All the papers mentioned belong at least to one of these fields: computer science, economics and psychology. Chapter 3 presents the model of decision making for our agents and the introduction of the simulations. This model is a Bayesian decision making algorithm based on the combination of the expected utility and the individual risk aversion of the agent player 1.

Chapter 4 summarizes some of the most interesting results of the simulations. Many simulations, following the parameters explained in Chapter 3, were performed. Out of all the data obtained some of the simulations have been selected and discussed in Chapter 4.

Using ABM, we have studied a trust game in which potentially risk-averse agents acting as Player 1 choose whether to trust or not in order to maximize their expected utility, given the probability of reciprocation by Player 2 agents in their neighbourhood or in the entire population.

Our main findings indicate the relevance of our approach to the co-evolution of risk attitudes and the trustworthiness of people in society. To begin with the findings, as expected, no matter the initial situation risk aversion grows to a level dictated by the likelihood of reciprocity and, thus, the trustworthiness of agents. The locality or global nature of interaction plays an important role. Local and global imitation has been tested in 4.5 and 4.8 and it has been congruent with the predicted in section 3.3.6. Risk aversion evolves together with trust and trustworthiness as observed in chapter 4. Moreover trust and trustworthisness evolve in parallel but risk evolves before convergence. The most important finding is that, in our model simulations, trust behaviour follows reciprocation attributes, and both tend to reach values close to 0.8 on average, as other empirical studies have reported. Risk aversion results from ‘mixed’ initial populations (Tversky and Kahneman 1992; Birnbaum and Chavez 1997; Abdellaoui 2000).

Other finding of these simulations is that societies who trust too much are in risk of being debilitated by selfish behaviours as stated in section 4.2. In the introduction chapter we state that trust improves efficiency in societies (Knack and Keefer 1997; Porta et al. 1997) but we did not foresee the opposite effect of trust in societies. These results of the simulations give us a clue about what happens when psychopathic leaders abuse the trust of their groups such as the emergence of Nazis before WWII or nowadays extreme right parties in many countries. In the same section 4.2. we state that risk aversion curbs the emergence of non-reciprocators, identifying one of the strongest findings of this thesis, the importance of coevolution. In simulations with only evolution of risk or only evolution of reciprocity the results are less similar to reality meanwhile with co evolution of both parameters we obtain results that are closer to experimental data.

Other findings are that the emergence of agents’ aggregation was found in the majority of the simulations and that societies which had bad performance in the past are found to have more difficulties to improve in the future (section 4.4).

Mutations introduced in 3.3.8. have been analysed in simulations 4.7, 4.8 and 4.9. This feature allows to tune the control of the simulations, through the likelihood of agent mutation, in order to avoid getting populations locked in local ESS, lose heterogeneity or allow them to adapt to shocks.

This research has some limitations, some of them because of the extension of the research itself and others related with the size of the data that must be analysed (1 TB). Measure sizes of the clusters, the amounts of clusters in the population or the density of clusters are the next steps in order to study and better understand the data obtained. It is difficult to get real data of psychopathic population in order to feed and validate the simulations. As stated in chapter 2, not all the non-reciprocators agents would be psychopaths but societies with higher amounts of psychopaths would have less reciprocators.

Another possible improvement consists of making the topology of the networks more complex based on dynamic networks. In these kind of topologies agents reinforce link connections whose interactions are beneficial for them and destroy or weaken links that are not profitable. Besides risk aversion and trutworhiness, other traits of human personality can be explored in the trust game by ABM simulations. Big Five traits can be included in the model. Also adapt the model in other games such as prisoner's dilemma, stag and hunt, ultimatum game and dictator game would be another option.

Besides risk aversion, humans have a different degree of optimism that affect their decisions. Further studies will include optimism of the agents in the model. This is already implemented in the simulations; it is a new variable epsilon that increases the probability of an agent to choose the trust strategy.

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CHAPTER 7.APPENDIX

7.1. ABMS description in XML

```
<?xml version="1.0" encoding="UTF-8"?>
<xmodel version="2" xmlns:xsi="http://www.w3.org/2001/XMLSchema-
instance"
xsi:noNamespaceSchemaLocation="http://flame.ac.uk/schema/xmml_v2.xsd">
    <name>model 01</name>
    <version>1</version>
    <author>Jose Guinot</author>
    <description>Circular Trust game playground whitout changes in
population, no dies no replication</description>
    <environment>
        <constants>
            <variable>
                <type>float</type>
                <name>equivalentecierto</name>
```

```
                <description>value wich determines if an agent decides
strategy</description>
            </variable>
            <variable>
                <type>int</type>
                <name>population</name>
                <description>population of the simulation</description>
            </variable>
        </constants>
        <functionFiles>
            <file>agent_a_match.c</file>
            <file>agent_a_play.c</file>
        </functionFiles>
    </environment>
    <agents>
        <xagent>
            <name>agent_a</name>
            <description>An agent that plays Trust game with its
neighbours</description>
            <memory>
```

```
                <variable>
                    <type>int</type>
                    <name>id</name>
                    <description>An integer variable ID unique from 1
to circle</description>
                </variable>
                <variable>
                    <type>int</type>
                    <name>money</name>
                    <description>An integer variable money
</description>
                </variable>
                <variable>
                    <type>int</type>
                    <name>partner</name>
                    <description>id left or id rigth </description>
                </variable>
                <variable>
                    <type>float</type>
                    <name>p</name>
```

```
                    <description>p continuous value describing the
agent Psicopath/Suspicious=0 Confident/Collaborative=1</description>
                </variable>
                <variable>
                    <type>int</type>
                    <name>role</name>
                    <description>role playing this
iteration</description>
                </variable>
            </memory>
            <functions>
                <function>
                    <name>match</name>
                    <description>Each agent send a message to one of
its neigbours</description>
                    <currentState>start</currentState>
                    <nextState>Play</nextState>
                    <outputs>
                        <output>
                            <messageName>message_z</messageName>
                        </output>
```

```
                    </outputs>
                </function>
                <function>
                    <name>play</name>
                    <description>if they agree play the
game</description>
                    <currentState>Play</currentState>
                    <nextState>end</nextState>
                    <inputs>
                        <input>
                            <messageName>message_z</messageName>
                            <filter>
                                <lhs>
                                    <value>a.id</value>
                                </lhs>
                                <op>EQ</op>
                                <rhs>
                                    <value>m.neig</value>
                                </rhs>
                            </filter>
```

```
                </input>

            </inputs>

        </function>

    </functions>

</xagent>

</agents>

<messages>

    <message>

        <name>message_z</name>

        <description>A message holding an id</description>

        <variables>

            <variable>

                <type>int</type>

                <name>neig</name>

                <description>id partner desired</description>

            </variable>

            <variable>

                <type>int</type>

                <name>remitent</name>

                <description>remitent  ID</description>
```

```
                </variable>
                <variable>
                    <type>float</type>
                    <name>premitent</name>
                    <description>remitent P</description>
                </variable>
            </variables>
        </message>
    </messages>
</xmodel>
```

7.2. Definition of a agent function: match

```
#include "header.h"
#include "agent_a_agent_header.h"
#include "time.h"

/*
```

```
 * \fn: int agent_a_do_matching()
 * \brief: send a message to the left or the rigth.
 */
//int agent_a_do_matching()
 int match()
{
 // send a message
 int size=POPULATION;
 int neig;
 time_t t;
 int aux=0;

 //srand((unsigned)t); SI INICIALIZO LA SEMILLA ME DA SIEMPRE EL MISMO
RESULTADO

 if (rand()>(RAND_MAX/2))
  aux=-1;
 else
  aux= 1;
 neig=ID+aux;
```

```
 if (neig>size) neig=1;

 if (neig<1) neig=size;

 add_message_z_message(neig,ID,P);

 PARTNER=neig;

 if (ID==1)

  printf ("*Soy el agente: %d  y quiero jugar con: %d  \n",ID ,neig);

 else

  printf  ("Soy el agente: %d  y quiero jugar con: %d  \n ",ID ,neig);


 return 0; /* Returning zero means the agent is not removed */

}
```

7.3. Definition of a agent function: play

```
#include "header.h"

#include "agent_a_agent_header.h"
```

```
/*
 * \fn: int agent_a_play_game()
 * \brief:recive message and play if is matched*/
int play()
{
 int remitente;
 float poponente;


 // Read messages of type message_z
 START_MESSAGE_Z_MESSAGE_LOOP
  remitente= message_z_message->remitent;
  poponente= message_z_message->premitent;
 FINISH_MESSAGE_Z_MESSAGE_LOOP
 if (remitente==PARTNER){
  //jugamos;
  //printf("Voy a jugar, soy agente: %d  dinero %d p %f\n",
ID,MONEY,P);
  if (ROLE==1)              //juega como tipo 1
  {
```

```
 if (EQUIVALENTECIERTO<P)
 {
   MONEY=MONEY+1;  //es psicopata y el oponente no importa
 }
 else
 {
  if(EQUIVALENTECIERTO>=poponente)
   MONEY=MONEY+2; //es confiado y su oponente tambien

  // else
   //No gana nada es confiado pero el oponente es psicopata
 }

}
else
{
 if (EQUIVALENTECIERTO<P) //psicopata
 {
  if(EQUIVALENTECIERTO<poponente)
   MONEY=MONEY+1;      //oponente  psicopata
```

```
    else
     MONEY=MONEY+3;      //oponente confiado
   }
   else      //confiado
   {
    if(EQUIVALENTECIERTO<poponente)
     MONEY=MONEY+1;    //oponente  psicopata
    else
     MONEY=MONEY+2;    //oponente confiado
   }
  }
  printf("Resultados del agente: %d  dinero %d pareja %d\n",
ID,MONEY,remitente);
 }
 //printf("Resultados del agente: %d  dinero %d p %f\n", ID,MONEY,P);
 if (ROLE==1)
 {
  ROLE=0;
 }
 else
```

```
 {
  ROLE=1;
 }

 return 0; /* Returning zero means the agent is not removed */
}
```

7.4. XML of the simulation's first iteration


```
<states>
<itno>1</itno>
<environment>
<equivalentecierto>0.500000</equivalentecierto>
<population>1024</population>
</environment>
<xagent>
<name>agent_a</name>
<id>1</id>
```

```
<money>0</money>

<partner>1024</partner>

<p>0.827620</p>

<role>0</role>

</xagent>

<xagent>

<name>agent_a</name>

<id>2</id>

<money>0</money>

<partner>1</partner>

<p>1.152144</p>

<role>1</role>

</xagent>

<xagent>

<name>agent_a</name>

<id>3</id>

<money>0</money>

<partner>2</partner>

<p>0.795266</p>

<role>0</role>
```

```
</xagent>
<xagent>
<name>agent_a</name>
<id>4</id>
<money>0</money>
<partner>3</partner>
<p>0.824442</p>
<role>1</role>
</xagent>
<xagent>
<name>agent_a</name>
<id>5</id>
<money>0</money>
<partner>6</partner>
<p>0.726833</p>
<role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
<id>6</id>
```

```
<money>0</money>

<partner>7</partner>

<p>0.782730</p>

<role>1</role>

</xagent>

<xagent>
```


…omitted code…


```
<xagent>

<name>agent_a</name>

<id>1022</id>

<money>1</money>

<partner>1023</partner>

<p>0.859830</p>
```

```
<role>1</role>
</xagent>
<xagent>
<name>agent_a</name>
<id>1023</id>
<money>1</money>
<partner>1022</partner>
<p>1.192997</p>
<role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
<id>1024</id>
<money>1</money>
<partner>1</partner>
<p>1.229483</p>
<role>1</role>
</xagent>
</states>
```

7.4.1. XML OF THE SIMULATION'S LAST ITERATION


```
<states>

<itno>10000</itno>

<environment>

<equivalentecierto>0.500000</equivalentecierto>

<population>1024</population>

</environment>

<xagent>

<name>agent_a</name>

<id>1024</id>

<money>3771</money>

<partner>1</partner>

<p>1.229483</p>

<role>0</role>

</xagent>

<xagent>
```

```
<name>agent_a</name>

<id>1023</id>

<money>3750</money>

<partner>1024</partner>

<p>1.192997</p>

<role>1</role>

</xagent>

<xagent>

<name>agent_a</name>

<id>1022</id>

<money>3741</money>

<partner>1023</partner>

<p>0.859830</p>

<role>0</role>

</xagent>
```


…omitted code…

```
<xagent>
<name>agent_a</name>
<id>3</id>
<money>3744</money>
<partner>4</partner>
<p>0.795266</p>
<role>1</role>
</xagent>
<xagent>
<name>agent_a</name>
<id>2</id>
<money>3746</money>
<partner>1</partner>
<p>1.152144</p>
<role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
<id>1</id>
```

```
<money>3736</money>

<partner>1024</partner>

<p>0.827620</p>

<role>1</role>

</xagent>

</states>
```


7.4.2. XML OF THE INITIAL CONDITIONS SIMILAR NEIGHBOURS


```
<states>

<itno>0</itno>

<environment>

<equivalentecierto>0.5</equivalentecierto>

<population>1024</population>

</environment>

<xagent>

<name>agent_a</name>
```

```
  <id>1</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.998046875</p>
  <role>1</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>2</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.99609375</p>
  <role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>3</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.994140625</p>
```

```
  <role>1</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>4</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.9921875</p>
  <role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>5</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.990234375</p>
  <role>1</role>
</xagent>
<xagent>
```

…omitted code…


```
<xagent>
<name>agent_a</name>
  <id>1022</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.99609375</p>
  <role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>1023</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.998046875</p>
  <role>1</role>
</xagent>
```

```
<xagent>
<name>agent_a</name>
  <id>1024</id>
  <money>0</money>
  <partner>0</partner>
  <p>1.0</p>
  <role>0</role>
</xagent>
</states>
```


7.4.3. XML OF THE INITIAL CONDITIONS WITH NOISE NEIGHBOURS


```
<states>
<itno>0</itno>
<environment>
<equivalentecierto>0.5</equivalentecierto>
<population>1024</population>
</environment>
```

```
<xagent>
<name>agent_a</name>
  <id>1</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.827620061215</p>
  <role>1</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>2</id>
  <money>0</money>
  <partner>0</partner>
  <p>1.15214401056</p>
  <role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>3</id>
  <money>0</money>
```

```
  <partner>0</partner>
  <p>0.795266266697</p>
  <role>1</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>4</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.824441730334</p>
  <role>0</role>
</xagent>
<xagent>
<name>agent_a</name>
  <id>5</id>
  <money>0</money>
  <partner>0</partner>
  <p>0.726832994118</p>
  <role>1</role>
</xagent>
```

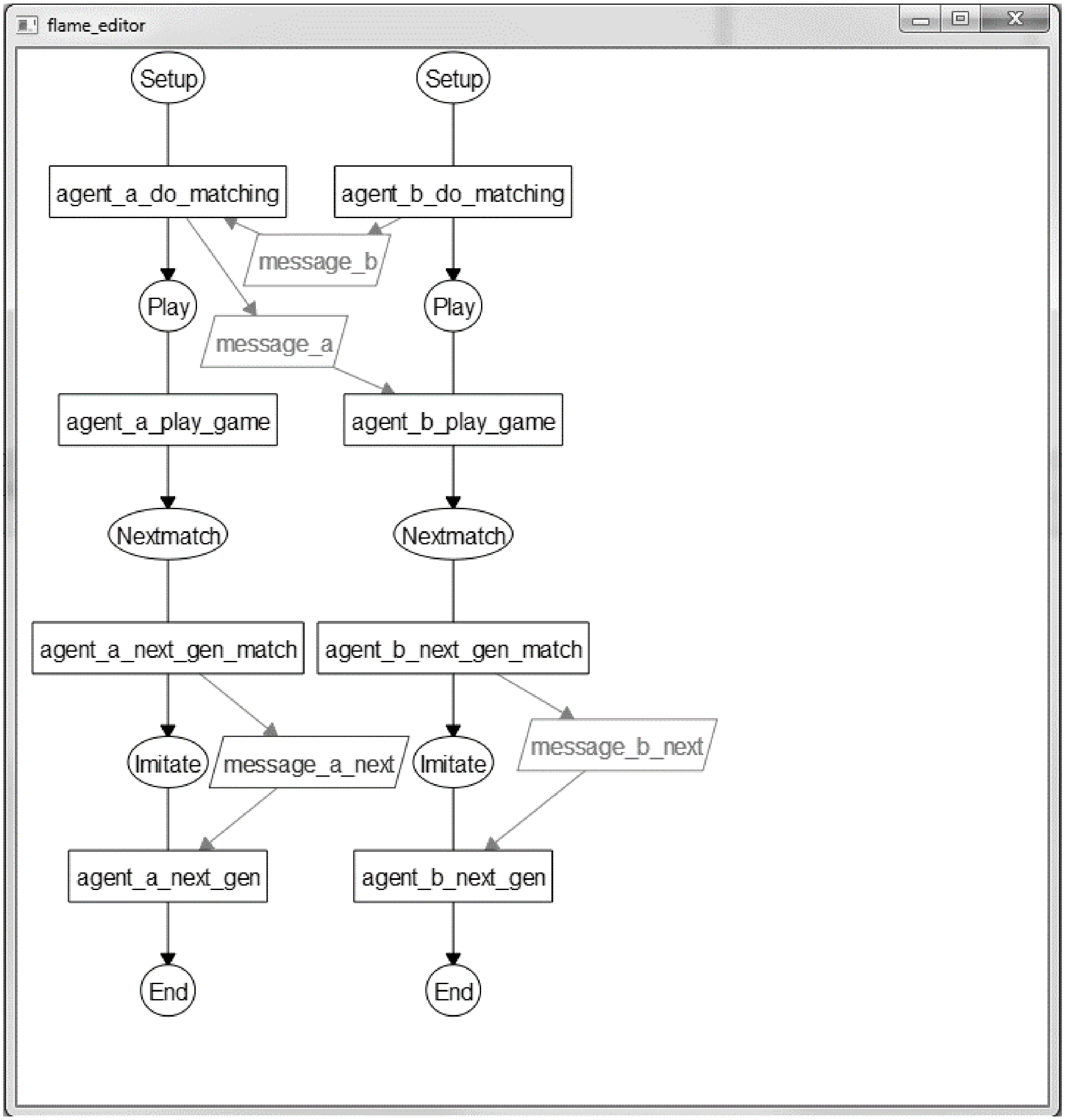
…omitted code…

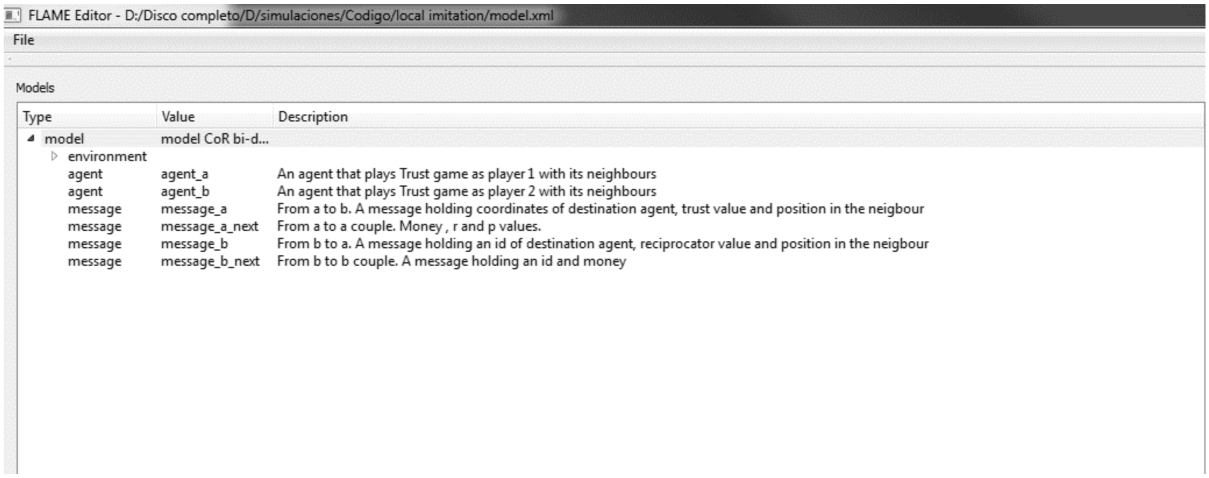

```
<xagent>

<name>agent_a</name>

  <id>1022</id>

  <money>0</money>

  <partner>0</partner>

  <p>0.859830282732</p>

  <role>0</role>

</xagent>

<xagent>

<name>agent_a</name>

  <id>1023</id>

  <money>0</money>

  <partner>0</partner>

  <p>1.19299675596</p>

  <role>1</role>

</xagent>

<xagent>
```

```
<name>agent_a</name>
  <id>1024</id>
  <money>0</money>
  <partner>0</partner>
  <p>1.22948322803</p>
  <role>0</role>
</xagent>
</states>
```


7.5. Parameters of the simulations

Model diagram


flame_editor
Setup
Setup
agent_a_do_matching
agent_b_do_matching
message_b
Play
Play
message_a
agent_a_play_game
agent_b_play_game
Nextmatch
Nextmatch
agent_a_next_gen_match
agent_b_next_gen_match
Imitate
message_a_next
Imitate
message_b_next
agent_a_next_gen
agent_b_next_gen
End
End


FLAME Editor - D:/Disco completo/D/simulaciones/Codigo/local imitation/model.xml

File

Models

Type	Value	Description
model	model CoR bi-d...	
environment		
agent	agent_a	An agent that plays Trust game as player 1 with its neighbours
agent	agent_b	An agent that plays Trust game as player 2 with its neighbours
message	message_a	From a to b. A message holding coordinates of destination agent, trust value and position in the neigbour
message	message_a_next	From a to a couple. Money , r and p values.
message	message_b	From b to a. A message holding an id of destination agent, reciprocator value and position in the neigbour
message	message_b_next	From b to b couple. A message holding an id and money

message_a   from a to b

Type	Name	Description
int	remitente	self ID
int	destposx	coordinate of the destination
int	destposy	coordinate of the destination
int	from	relative position of the remitent
int	trust	agent says if is going to trust

message_a_next from a to next

Type	Name	Description
int	id	id remitent
int	money	money of the remitent
float	p	remitent p
float	r	remitent r

message_b from be to a

Type	Name	Description
int	remitente	self ID
int	destposx	coordinate of the destination
int	destposy	coordinate of the destination
int	id_from	id remitent
int	reciprocator	reciprocator or not

message_b_next from b to b

Type	Name	Description
int	id	id of agent
int	reciprocator	reciprocator or not
int	money	money of the remitent

Environmet variables

Memory

Type	Name	Description
int	population	population of the simulation
int	width	columns of the simulation 2D arrangement
int	radius	distance between agents in order to compare imitate the best
float	h	payoff for player 2 when do not reciprocate
float	y	payoff for player 1 and 2 when trust and reciprocate
float	x	payoff for player 1 and 2 when player 1 do not trust
float	l	payoff for player 1 when he is not reciprocated
int	num_era	times to play each era, for now multiple of 4
int	max_generations	number of eras/generations of the simulation

Agent a

Transition Functions

Current State	Input	Condition	Function Name	Mpost	Output	Next State	Description
Setup	message_b filter((a.posx == m.destposx) AND (a.posy == m.destposy))		agent_a_do_matching		message_a	Play	Each agent a recives reciprocator values and send his r and p value to its neigbours
Play			agent_a_play_game			Nextmatch	if they agree play
Nextmatch			agent_a_next_gen_match		message_a_next	Imitate	send a message to the board with money, r and p values. And decides his couple.
Imitate	message_a_next filter(a.couple == m.id)		agent_a_next_gen			End	recives message from couple, compares and imitates if it is necesary

Type	Name	Description
int	id	An integer variable ID for each agent
int	idmatrix	An integer variable ID for each agent, arranged with the other players
int	posx	Coordinate x
int	posy	Coordinate y
int	money	An integer variable money
float	r	risk attitude
float	p	relatives reciprocity average
int	trust	what strategy is taking this agent in this neigbourhood
int	reciprocators[4]	values for reciprocators in order from 0 to 3 they are booleans value p (probability of being reciprocted) is going to be: (p[0]+p[1]+p[2]+p[3])/4
int	couple	to who is going to listen messages in order to compare and imitate

Agent b

Current State	Input	Condition	Function Name	Mpost	Output	Next State	Description
Setup			agent_b_do_matching		message_b	Play	Each agent send a message to one of its neigbours
Play	message_a filter((a.posx == m.destposx) AND (a.posy == m.destposy))		agent_b_play_game			Nextmatch	agents play
Nextmatch			agent_b_next_gen_match		message_b_next	Imitate	send a message to the board with money and reciprocate. And decides his couple.
Imitate	message_b_next filter(a.couple == m.id)		agent_b_next_gen			End	recives message from couple, compares and imitates if it is necesary

Type	Name	Description
int	id	An integer variable ID for each agent
int	idmatrix	An integer variable ID for each agent, arranged with the other players
int	posx	Coordinate x
int	posy	Coordinate y
int	money	An integer variable money
int	partner[4]	partner's trust 0 north 1 east 2 south 3 west
int	reciprocator	1 or 0
int	couple	who is going to be compared to this agent

Model Epsilon localimitation

Type	Value
version	1
author	Jose Guinot
description	Trust game, imitate the best both players, Von Neumann neihgbourhood 1. (h,y,x,l)=(30,20,10,5)

model	model CoR bi-dimensional	
environment		
agent	agent_a	An agent that plays Trust game as player 1 with its neighbours
agent	agent_b	An agent that plays Trust game as player 2 with its neighbours
message	message_a	From a to b. A message holding coordinates of destination agent, trust value and position in the neigbour
message	message_a_next	From a to a couple. Money , r and p values.
message	message_b	From b to a. A message holding an id of destination agent, reciprocator value and position in the neigbour
message	message_b_next	From b to b couple. A message holding an id and money

A

Transition Functions

Current State	Input	Condition	Function Name	Mpost	Output	Next State	Description
Setup	message_b filter(a.id == m.dest)		agent_a_do_matching		message_a	Play	Each agent a recives reciprocator values and send his r and p value to its neigbours
Play			agent_a_play_game			Nextmatch	if they agree play
Nextmatch			agent_a_next_gen_match		message_a_next	Imitate	send a message to the board with money, r and p values. And decides his couple.
Imitate	message_a_next filter((a.couplex == m.posx) AND (a.coupley == m.posy))		agent_a_next_gen			End	recives message from couple, compares and imitates if it is necesary

Memory

Type	Name	Description
int	id	An integer variable ID for each agent
int	epsilon	Value of an optimism/pesimism for each agent
int	posx	Coordinate x
int	posy	Coordinate y
int	money	An integer variable money
float	r	risk attitude
float	p	relatives reciprocity average
int	trust	what strategy is taking this agent in this neigbourhood
int	reciprocators[4]	values for reciprocators in order from 0 to 3 they are booleans value p (probability of being reciprocted) is going to be: (p[0]+p[1]+p[2]+p[3])/4
int	couplex	to who is going to listen messages in order to compare and imitate
int	coupley	to who is going to listen messages in order to compare and imitate

B

Transition Functions

Current State	Input	Condition	Function Name	Mpost	Output	Next State	Description
Setup			agent_b_do_matching		message_b	Play	Each agent send a message to one of its neigbours
Play	message_a filter(a.id == m.dest)		agent_b_play_game			Nextmatch	agents play
Nextmatch			agent_b_next_gen_match		message_b_next	Imitate	send a message to the board with money and reciprocate. And decides his couple.
Imitate	message_b_next filter((a.couplex == m.posx) AND (a.coupley == m.posy))		agent_b_next_gen			End	recives message from couple, compares and imitates if it is necesary

Memory

Type	Name	Description
int	id	An integer variable ID for each agent
int	posx	Coordinate x
int	posy	Coordinate y
int	money	An integer variable money
int	partner[4]	partner's trust 0 north 1 east 2 south 3 west
int	reciprocator	1 or 0
int	couplex	who is going to be compared to this agent
int	coupley	who is going to be compared to this agent

Message a

Memory

Type	Name	Description
int	remitente	self ID
int	dest	coordinate of the destination
int	from	relative position of the remitent
int	trust	agent says if is going to trust

Message a next

Type	Name	Description
int	posx	id remitent x
int	posy	id remitent y
int	money	money of the remitent
float	p	remitent p
float	r	remitent r

Message b

Type	Name	Description
int	remitente	self ID
int	dest	ID of the destination
int	id_from	id remitent relative in position 0 south, 1 east, 2 north, 3 west
int	reciprocator	reciprocator or not

Message b next

Type	Name	Description
int	posx	id x axis
int	posy	id y axis
int	reciprocator	reciprocator or not
int	money	money of the remitent

7.6. Scripts

7.6.1. LAUNCH SIMULATIONS (LAUNCH.BAT):

```
@echo off
title Launching simulations
:principio
set/p cant=How many generations?
set/a contador=%cant%
set/p carpetas=Folder?
title  %carpetas% is being simulated
set total=0
if %cant% LSS 2 (goto mal) else (goto bucle)
:mal
echo It has to be greater or equal to 2
goto principio
:bucle
echo Count value is: %contador%
CD
CALL main 100 %carpetas%%contador%/poblacion.xml -f 100
set/a contador=%contador%-1
if not %contador% == 0 (goto bucle)
echo.
echo Finished
pause >nul
echo MsgBox "Simulations done",64, "End of simulations">%temp%\mensaje.vbs
start %temp%\mensaje.vbs
```

7.6.2. EXTRACT AVERAGE TIME SERIES (EXTRACT_TSERIES.BAT)

```
@echo off
echo Bienvenido %username%, deseas continuar?
pause>nul
@echo off
title Let's
:principio extract r, trust , reciprocators and money.
set/p cant=How many generations are there?
set/a contador=%cant%
set/p carpetas=Name of the folders?
title Extracting from  %carpetas% .
set total=0
if %cant% LSS 2 (goto mal) else (goto bucle)
:mal
echo Greater of equal than 2 please.
goto principio
:bucle
echo Count value is: %contador%
CD
CALL grep "<r>" %carpetas%%contador%\100.xml|awk 'sub("\\<r\\>","",$0)'|awk 'sub("\\</r\\>","",$0){aux=$1; suma=suma+aux; cuadrador=cuadrador+(aux*aux)}END{print suma" "cuadrador}'>>%carpetas%_res_r.txt
CALL grep "<trust>" %carpetas%%contador%\100.xml|awk 'sub("\\<trust\\>","",$0)'|awk 'sub("\\</trust\\>","",$0){aux=$1; sumat=sumat+aux; tcua=tcua+(aux*aux)}END{print sumat" "tcua}'>>%carpetas%_res_trust.txt
CALL grep "<reciprocator>" %carpetas%%contador%\100.xml|awk 'sub("\\<reciprocator\\>","",$0)'|awk 'sub("\\</reciprocator\\>","",$0){aux=$1; recipcua=recipcua+(aux*aux); sumarecip=sumarecip+aux}END{print sumarecip" "recipcua}'>>%carpetas%_res_reciprocators.txt

CALL grep "<money>" %carpetas%%contador%\100.xml|awk 'sub("\\<money\\>","",$0)'|awk 'sub("\\</money\\>","",$0){suma=suma+$1}END{print suma/10000}'>>%carpetas%_res_money.txt

set/a contador=%contador%-1
if not %contador% == 0 (goto bucle)
echo.
echo Finalizado
```

```
pause >nul n
echo MsgBox "Finished",64, "Simulations done">%temp%\mensaje.vbs
start %temp%\mensaje.vbs
```

7.6.3. EXTRACT PARAMETERS FROM A POPULATION (EXTRACT.BAT)

```
@echo off
title We are going to extract r r,trust, reciprocator and coordenates.
Echo File: %1
:principio
cd %2
CALL grep "<r>" %1.xml|gawk 'sub("\\<r\\>","",$0)'|gawk 'sub("\\</r\\>","",$0){print $1}'>> ..\results\%1%2r.txt
CALL grep "<trust>" %1.xml|gawk 'sub("\\<trust\\>","",$0)'|gawk 'sub("\\</trust\\>","",$0){print $1}'>> ..\results\%1%2trust.txt
CALL grep "<posx>" %1.xml|gawk 'sub("\\<posx\\>","",$0)'|gawk 'sub("\\</posx\\>","",$0){print $1}'>> ..\results\%1%2posx.txt
CALL grep "<posy>" %1.xml|gawk 'sub("\\<posy\\>","",$0)'|gawk 'sub("\\</posy\\>","",$0){print $1}'>>..\results\%1%2posy.txt
CALL grep "<reciprocator>" %1.xml|gawk 'sub("\\<reciprocator\\>","",$0)'|gawk 'sub("\\</reciprocator\\>","",$0){print $1}'>> ..\results\%1%2reciprocator.txt
CALL grep "<id>" %1.xml|gawk 'sub("\\<id\\>","",$0)'|gawk 'sub("\\</id\\>","",$0){print $1}'>> ..\results\%1%2id.txt
CALL grep "<money>" %1.xml|gawk 'sub("\\<money\\>","",$0)'|gawk 'sub("\\</money\\>","",$0){print $1}'>> ..\results\%1%2money.txt
cd ..
echo Finalizado
```