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An evolutionary agent-based model of the interplay between punishment and damaging behaviours

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Abstract
The article aims at contributing to the discussion about the relationships between ICT, computer science and policy-making by using an agent-based social simulation. Enabled, from a technical point of view, by development of Distributed Artificial Intelligence in the 1990s and by the features of the object-oriented programming paradigm, social simulations are a tool for the analysis of social dynamics that can be used also to support the design and the evaluation of public policies. After a brief description of social simulation paradigm and its impact on social sciences, the paper presents a simple agent-based model devised to analyze, even if in a very abstract way, a phenomenon that can rouse the interest of legal scientists: the interplay between damaging behaviours, punishment and social mechanisms of learning and imitation. Our goal is to show how agent-based simulation can be used not only to illuminate basic mechanisms underlying social phenomena but also to reflect, in an innovative way, on how society, policy and rule makers can deal with them.

1. Agent-based models: a computational tool to understand (and manage) social complexity

After the invention of electronic computers, the role played by computational techniques in the social sciences (here defined as the ensemble of disciplines investigating human and social dynamics at all levels of analysis, from individual cognition to international organizations) has become more and more important. From the second half of the 20th century, social scientists have progressively learned to exploit advanced instruments of computation to gain a deeper understanding of the social world. The emerging methodological paradigm of computational social science (Lazer et al. 2009), a "fledging interdisciplinary field at the intersection of the social sciences, computational science, and complexity science" (Cioffi-Revilla 2010a), is gradually changing the way in which social phenomena are investigated and managed. The set of computational social science methods is wide and encompasses different techniques: automated information extraction; social network analysis; geo-spatial analysis; complexity modeling and social simulations models, each of which has several specialized branches.

In this paper we focus on agent-based simulation models (ABM), a specific kind of social simulation (Gilbert and Doran 1994; Conte et al. 1997; Epstein 2006; Gilbert 2008) that can be considered, from a technical point of view, the result of a turning point in the history of artificial intelligence: the rise of Distributed Artificial Intelligence (O'Hare 1996). In general terms, ABM can be defined as a "computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment" (Gilbert 2008). Based on the identification of the scientific explanation with the reproduction "*in silico*" (i.e., in a computer simulation) of the social processes being investigated, ABM has contributed to promote a generative approach to social science research: social macro-dynamics and structures are interpreted, described, reproduced and explained as the result of micro-interactions between computational entities (agents) simulating the behaviour of real individuals. In this perspective, modelling the structural properties of social systems and exploring their spatio-temporal development via computer simulation are crucial steps to provide explanations of complex social outcomes. Agents are distinct parts of a computer program that may contain different variables, parameters, and behaviours. Agents interact by exchanging information, react to the environment (programmed to mimic the real social world in more or less detail), learn, adapt, and change rules of behaviour showing cognitive and behavioural properties typical of human agents.

From the epistemological point of view, the impact of agent-based modeling is relevant (Squazzoni 2009; Frank et al. 2009): ABM is establishing the primacy of modelling for social science descriptions and theorizing, in contrast with the prevalent use of narrative descriptions that dominate (with the exception of economics) most social science (Franck 2002). Moreover ABM has "strengthened an 'issue-oriented' style of research that is favoring trans-disciplinary collaboration and stepping over the classic social science disciplinary boundaries" (Squazzoni 2010). According to this approach, a growing community of social scientists investigates topics spanning from cooperation (Axelrod 1997) to reputation (Conte and Paolucci 2002), from the emergence of conventions (Hodgson and Knudsen 2004) to the evolution of institutions (Cioffi-Revilla et al. 2007) and the emergence of social norms (Conte and Castelfranchi 1995; Epstein 2001; Andrighetto et al. 2007), with interesting results.

The potentials of ABM are not only limited to analytical purposes as they provide insights of social behaviours that can inform the design of policy solutions: as a matter of fact, an interesting feature of agent based model is their capacity to support the development of innovative and policy instruments. Traditional policy models often fail their purpose being unable to grasp and forecast complex social processes including the reaction of agents to policy decisions, the aggregate effect of their interactions, and their consequences on large spatial-temporal scales (Moss 2002, Squazzoni and Boero 2010). Apart from interesting experiences of policy applications in the economy (Buchanan 2009; Farmer and Foley 2009) and the examples of ABM applications to manage socio-ecological systems at a community level (Etienne et al. 2003; Bousquet et al. 2005), there are several research projects witnessing the growing interest towards the potentialities of agent based simulations in studying the impact of (and in designing a) public policy. Some examples are research projects such as *FuturICT* (http://www.futurict.eu), *Eurace* (Deissenberg et al. 2008) and *Riftland* (http://goo.gl/jrLLN), specifically aiming to design and implement complex agent-based models devoted to support design policies and to manage economic and social phenomena.

Even if it belongs to the area of social sciences, legal science has substantially fallen behind in this research using agent based models. Yet, as we will highlight below, there are various reasons for legal scientist to look at ABM: not only, in general terms, because they can contribute to illuminate social dynamics that are relevant for law but also, more specifically, because fundamental legal issues and procedures such as norm making and regulatory impact analysis are important components of policy making that ABM may support.

The idea of using computational artefacts for the investigation of socio-legal phenomena, indeed, dates back to the ’40s of the last century (Loevinger 1949; Baade 1963). Computer simulations, in particular, have been repeatedly described as a viable tool to support legal analysis (Degnan and Haar 1970; Drobak 1972; Aikenhead et al. 1997) and the study of social phenomena linked to the functioning of legal systems and institutions (Van Baal 2004; Bosse and Gerritsen 2010), especially in the more empirically oriented discipline of criminology (Liu and Eck 2008). However, agent-based models still appear to be outside the horizon of most legal scientists. It is therefore important to promote in the legal field the design and implementation of simulation models in order to take confidence with this technique. In this prospect, the goal of this paper is to show how agent-based simulations can be used not only to illuminate in an innovative way the basic mechanisms underlying social phenomena, but also to reflect on how society can deal with them. Even when extremely simplified, social simulations model can indeed provide ideas for designing new policies and for examining the possible consequences of these policies.

2. Simulating the interplay between damaging behaviours and punishment

In order to explore the potential of ABM in dealing with phenomena that are relevant for law and legal science, we propose a simulation model of a wide class of human behaviours that we define as “other-damaging behaviours”.

Human beings often exhibit behaviours that damage others and societies must find ways to contain these behaviours to avoid disintegration in that the costs of living together become greater than the benefits. To better understand the importance of containing other-damaging behaviours for the continuing existence of a society, we have to consider the benefits of living socially. Many animals live socially, with frequent interactions among individuals and socially coordinated behaviours, but human beings are perhaps the most social of all animal species: they do not only constantly interact with one another and exhibit socially coordinated behaviours but, unlike nonhuman animals, they obtain most of what they need not from nature but from other individuals through the exchange of goods and they benefit from the knowledge and judgment of other individuals. In addition, human communities create a “central store” of resources, the State, to which all individuals in the community contribute and from which all individuals benefit (Parisi 1997). And, finally, human beings are cultural animals, that is, they learn most of their behaviours from others, and learning from others allows them to behave in similar ways, which is important in order to be able to predict how other individuals will behave and how they will respond to one's behaviour.

But an intense social life has its problems. Human beings may exhibit behaviours that increase the well-being of their authors but damage, i.e., decrease the well-being of either specific other individuals or the entire community. These "other-damaging" behaviours, if left unchecked, can become so frequent and diffused that the advantages of living together may be exceeded by the disadvantages of being damaged by others, and this may put the very existence of the society into question. Therefore, for any minimally complex human society it is necessary to include mechanisms that induce its members to refrain from exhibiting behaviours that damage others.

While other-damaging behaviours exist in all human societies, these behaviours and the mechanisms for containing them vary in different societies and in different epochs. This set of mechanisms, encompassing social norms, reputational sanctions, law enforcement, and even religion, are studied by disciplines spanning from psychology to anthropology, from sociology to political science, from history to criminology.

Law is especially concerned with the phenomenon. Legal systems have been always engaged in the containment of damaging behaviours: one of the most important statutory enactments of Roman private law, just to give a simple but meaningful example, is the *Lex Aquilia de damno* (Zimmermann 1996), a plebiscite enacted in the 3rd century BC dealing exactly with the "*damnum iniuria datum*" ("damage unlawfully inflicted"). The investigation of the mechanisms involved in the emergence and in the containment of damaging behaviours should therefore stimulate the interest of legal scientists, at least the ones belonging to those schools of thought, such as Legal Realism (Llewellyn 1962) or Institutionalism (Hauriou 1933; MacCormick and Weinberger 1986; La Torre 1993) that are interested in the empirical dimension of legal phenomena and try to approach it with an interdisciplinary orientation. Legal science, on the other hand, can be interpreted not only as the exegesis of legal rules or the definition and systematization of abstract legal concepts, but also as the analysis of the empirical processes which underlie legal phenomena. From this perspective agent-based models, with their capacity to support the understanding of the micro-foundations of complex social phenomena, seem to be a viable tool to study the interplay between legal and non legal phenomena (e.g. social norms and their dynamics), an issue that is sparking a growing interest among legal scholars (Posner 2000, Tamanaha 2001).

Taking cue from the considerations so far sketched, we focused on one of the most relevant mechanisms to contain other-damaging behaviours: the mechanism of sanction/punishment usually implemented by legal systems and by the State. More specifically, we have developed an agent-based model that aims to explore how the effect of punishment is affected by other factors like the opportunity to increase one's well-being without the risk of sanctions, by the mechanisms of imitation driven by social relations and, more in general, by the adaptive capabilities that push human beings to maximize their well-being.
The simulations, realized using the agent-based modelling environment *Netlogo* (Sklar 2007) and accessible on line at http://goo.gl/yRQ9r (figure 1), are

extremely abstract with respect to the complex set of factors, first of all cognitive factors, that play a role in the phenomena under investigation. Even if, as noted by the anthropologist E. Adamson Hoebel (1954), “norms are mental constructs” and even if several interesting simulation models of cognitive processes underlying norm compliance and transmission have been developed (Castelfranchi et al. 1998; Saam and Harrer 1999; Epstein 2001; Burke 2006; for an extensive reviews see Neumann 2010a 2010b), we preferred to avoid the simulation of complex mental constructs choosing instead a simple operational approach that postulates more directly observable entities and processes and tries to more directly capture the empirical phenomena of interest.

The concepts in terms of which we will analyse the phenomena we are talking about are essentially two: “other-damaging behaviour” and “punishment”. “Other-damaging behaviours” are behaviours that reduce the well-being of specific other individuals or of the entire community. “Punishment” is any behaviour on the part of other individuals or of some central authority that tries to decrease the probability that an individual will exhibit other-damaging behaviours in the future.

The simulations are extremely simplified and abstract with respect to the actual phenomena but, even being aware of this limit, we think they can help to look at those same phenomena in a different and more operational perspective. It is worth noting that simulation modelling can be used not only to make predictions or to explain existing empirical data, but also to illuminate “core dynamics”, to “discover new questions” and to “promote a scientific habit of mind” (Epstein 2008; on the exploratory nature of simulations, see Casti 1997; Grüne-Yanoff and Weinrich 2010). In doing so computer simulation models offer, among other things, a unique opportunity to go beyond disciplinary divisions: as we have said, other-damaging behaviours are studied by a number of distinct disciplines (i.e. law, sociology, psychology, etc.) and simulations help us in understanding how the phenomena studied by these different disciplines work together and influence each other.

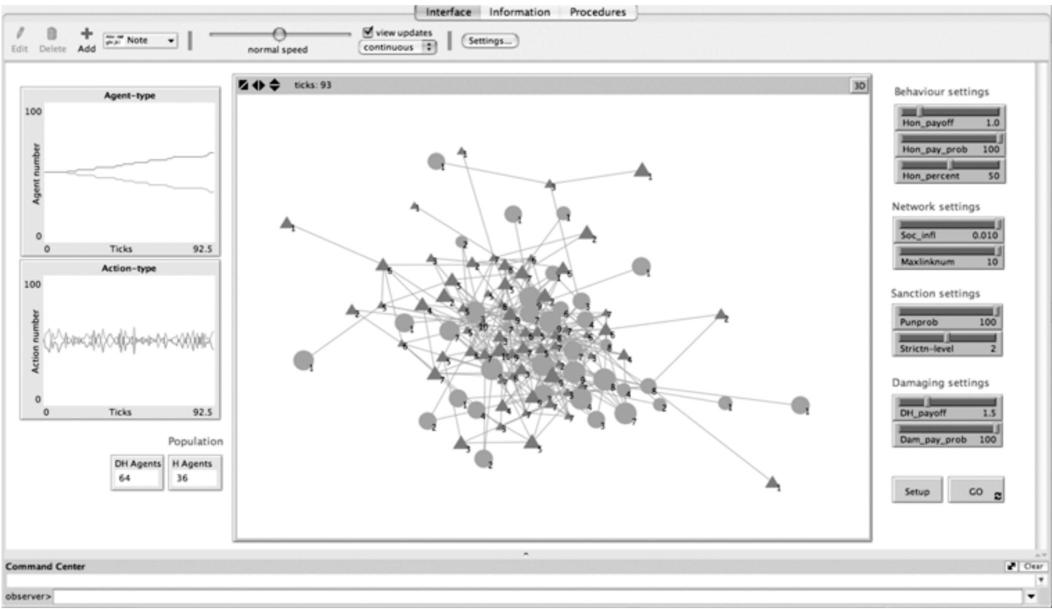

Fig. 1 - Screenshot of the Netlogo Simulation Environment

2.1 Theoretical framework

Before presenting in detail our model and the results of the experiments made using it, we briefly outline the theoretical framework which our research is based on. The analysis is split in two parts concerning, respectively, the approach to computer simulation modelling, and the theoretical assumptions underlying the way in which we have described, in the model, the social dynamics under investigation.

2.1.1 Simulation modelling approach

Every simulation is based on a model: a more or less abstract and simplified representation of a target phenomenon that accounts for its known or inferred properties. The design of the model and the way in which facts are stylized inside the model are crucial issues that can undergo significant variations depending on the research objectives, the scientific approach, and the researcher's point of view about the causes that play a role in the production of the phenomenon under investigation.

During its history, social research has produced different approaches to simulation modelling such as system dynamics (Forrester 1968; Randers 1980, Sterman 2000), microsimulations (Spielauer 2011), and agent-based simulations (Gilbert 2008; Epstein 2006), focusing on different aspects of reality. Within each of these approaches, different techniques have been then defined to stylize, formalize and operationalize social facts. In particular, research using agent-based social simulation has generated different approaches to modelling phenomena that are very close to those discussed in this paper such as the effects of punishment on cooperation, norms emergence, and norm compliance. These approaches, roughly speaking, can be classified into two macro-categories.

On the one hand, there are simulation models whose main objective is the analysis of the cognitive and sociocognitive underpinnings of human behaviours. This category of models, in which agents are endowed with complex cognitive architectures - BDI (*Beliefs, Desires, Intentions*) (Rao and Georgeff 1995) and BOID (*Beliefs, Desires, Obligations, Intentions*) (Broersen et al. 2001) - has achieved relevant and promising results (Neumann 2008a 2008b, 2010; Hollander and Wu 2011). On the other hand, there are evolutionary models which are somehow bio-inspired and are not so much interested in the internal dynamics of the agent but focus on the effects of mutual influences between individuals and the social environment and on analysing the condition under which pre-programmed strategies can become stable pattern of behaviour.

So far, evolutionary simulation models have been frequently used to understand how social outcomes spanning from cooperation (Axelrod 1984, 1997; Gintis et al. 2003; Heinrich and Heinrich 2007; Tomasello 2009) to migration dynamics (Barbosa et al. 2011), from social learning (Macy 1996) to network diffusion (Lahiri and Cebrian 2010) and survival strategies (Cecconi and Parisi 1998), can be explained as the result of adaptation strategies. The study of punishment, in particular, has already exploited evolutionary models (Boyd and Richerson 1992; Boyd et al. 2003; Fowler 2005; Hauert et al. 2007).

From a technical point of view, the core of the evolutionary approach is represented by modelling and programming techniques trying to mimick natural processes of adaption. One of the most relevant of these techniques is the genetic algorithm (GA) that imitates the evolutionary process of learning based on research and exploration (Holland 1992, 1995, 1998; Mitchell 1998). Often used in social simulation research (Pinata 2002; Chmura et al. 2007), GA allows to model populations of adaptive agents that are not fully rational in the sense that they are only capable of refining the strategies adopted by trials and errors. Using the selective reproduction of agents and the constant addition of random mutations, most effective strategies can emerge thanks to the research conducted by a succession of generations of agents.

According to this second approach, we used a genetic algorithm to simulate learning, where learning occurs across a succession of generations of agents rather than during an agent's life. Obviously, we interpret our genetic algorithm not in biological but in cultural terms (Reynolds 1994). An agent is a "model" which is imitated by a greater or smaller number of imitators that add some random variation to what they learn. We describe two sets of simulations. In the first set (Simulation 1) an agent learns from its "model" at the beginning of its life and then its behaviour remains the same for the agent's entire life. In the second set of simulations (Simulation 2) an agent, in addition to imitating its "model" at the beginning of its life, may also learn by imitating the agents with which it interacts during its life.

2.1.2 Sociological background

As we will see in more detail in the following sections, the most relevant dynamics of our simulation, the variation in the probability that an agent damages another agent, is the result of the interaction between different variables of the artificial society that stylise real phenomena we assume have a role in the interplay between punishment and damaging behaviours. Far from being the result of arbitrary assumptions, the choice and implementation of each of these variables and the fundamental rules according to which they interact are grounded in sociological theories of crime and deviance covering both individual and social dimension of the model. The variables are:

1. *Probability and severity of punishment*
2. *Payoff of damaging actions*
3. *Payoff of non-damaging behaviours*
4. *Behavioural trend (damaging/non damaging) prevailing in the social network*
5. *Number of members of the social network to which the agents belong.*

Here below a brief analysis of the theoretical background underlying the choices made in designing the model is proposed.

a) Rational choice theory

Design choices summarized in points 1 and 2 have been inspired by the theory of rational choice developed by the economist Gary Becker (1968). Widely used to model and investigate human decision making in economics, sociology, and political science, rational choice theory has been frequently employed in study of crime and deviance (Cornish and Clarke 1986a, 1986b; Clarke and Felson 2004). The basic idea of the theory is that people make decisions about how they should act by comparing the costs and benefits of different courses of action. When applied to criminal behaviour, the assumption entails that individuals decide whether or not to commit a crime on the basis of a cost-benefit analysis. According to this approach, Becker describes the amount of offences with the following function:

$$O = O\ (p, f, u)$$

where O is the number of offences committed by an individual in a given time, p is the probability of punishment, f is the entity of punishment, and u is a variable that encompasses all the other factors that can influence the decision. The probability of being punished (p), as well as the amount of the punishment (f) represent the hypothetical costs of the criminal behaviour, while the other factors (u) are made up of the benefits that flow from the commission of criminal acts. This means that the frequency of damaging behaviour is directly proportional to the benefits that can be drawn from the deviant/damaging action and inversely proportional to the severity of punishment.

The design of our model is substantially consistent with the assumptions of rational choice theory since the likelihood of damaging actions (a) increases with the benefits of damaging actions, and (b) decreases with the probability and severity of sanctions. We have also taken into account the criticism against rational choice theory due to the fact that human beings are not perfectly rational agents and often behave in a way that does not allow them to maximize their profit (see, among others, Paternoster and Bancman 2001; Piquero and Tibbets 2002; Clarke and Felson 2004; Cornish 2004). The agents of our simulation do not behave in a perfectly rational way: they gradually learn to maximize their profit thanks to the genetic algorithm but they can make errors and, in the social version of the model, they are also conditioned by imitation dynamics that introduce biases in their behavioural choices.

b) Strain theory

The design of the interaction between damaging behaviours and the variables described in point 3 above is grounded in the strain theory developed by the American sociologist Robert K. Merton (1949). Greatly simplifying, his theory traces the origins of deviance to the tensions that are caused by the gap between cultural goals and the means people have available to achieve those goals. Deviance is driven by the presence, in the society, of two different criminogenic factors that can push (strain) individuals to exhibit rule-breaking behaviours:

- High socio-economic aspirations, so called “cultural goals”
- Lack of socially approved means to achieve these aspirations.

Given this premise, Merton, argues that individuals tend to commit crime when society does not offer them the opportunity to realize their aspirations by acting in a manner consistent with institutional norms. According to this assumption, it is reasonable to assume that a high probability of success and high profitability of “legitimate” sources of income will result in a reduction in the level of deviance.

Our model is coherent with the assumption made by strain theory. Thanks to the evolutionary mechanism implemented by means of the genetic algorithm, the number of damaging actions (and, therefore, the number of dishonest agents) tends to decrease when the payoff and the probability of success of non-damaging actions increase, i.e., when the opportunities of a “lawful” gain grow.

c) Theories of social context
Several sociological theories argue that the causes of deviant behaviour have to be sought in the social context of which the individual is a part. Crime and deviance, in this theoretical perspective, are not the result of a rational choice or of a psychobiological predisposition but a "social fact", the result of conditions that "predispose individuals and groups to predictable results" (Matza and Sykes 1961): the individual is less important than the social context that imposes upon him or her certain actions, with or without his or her consent. This basic idea, for the first time proposed by Èmile Durkheim (1964), has been explored and refined several times producing two group of theories of crime, social control theories and learning theories, that have inspired the design of social interactions in our simulation model. According to social control theories, human beings are driven by selfish impulses that can be limited only through the internalization of norms that prevent deviant behaviours (Hirschi 1969; Sampson and Laub 1993; Williams and McShane 1994). This social control is made possible, among other things; by the attachment of the individual to people (e.g. parents, teachers, religious leaders etc.) that convey conformist values such as the respect for social and legal rules. The more a person is connected to this kind of persons, the less it is inclined to exhibit behaviors that would be stigmatized. Conversely, the more one is bound to subjects that do not carry values of norm compliance, the greater the propensity to deviate and commit crimes.

Interesting insights about the relationship between deviance, crime, and social context are offered also by social learning theories according to which the formation of one’s identity is a learned response to social stimuli. From this perspective, deviant and criminal behaviour is the result of a learning process that takes place when individual associates with other persons engaging in crime. Significantly, association with delinquent friends is the best predictor of delinquent behaviour other than prior delinquency. Among the scholars who have joined this school of thought (Cressey 1953; Matza and Sykes 1961) it is worth mentioning Edwin Sutherland, author of the so called “differential association theory” (Sutherland 1937, 1947; Sutherland and Cressey 1978) according to which criminal behaviour is not inherited or a result of any other biological condition but is learned through the interaction with other persons in a process of communication that involves first of all the members of the social network of which the individual is part. The group suggests not only techniques of committing the crime but also the specific direction of motives, drives, rationalizations, and attitudes, providing ways ("definitions") of understanding what is permissible and what is not. Based on this assumption, an individual becomes delinquent when, in the process of learning, "definitions" favorable to the violation of the law exceeds the definitions favorable to violation of the law (so-called principle of differential association).

The design of social interactions of our simulation model is linked with some of the assumptions made by the theories of social control and the theories of learning. A prevalence of dishonest agents in an agent's network will result in an increased likelihood that the agent will exhibit dishonest behaviours. Conversely, a prevalence of honest agents will increase the chances of exhibiting honest behaviours.

The choices made in designing the model in the light of the theories mentioned in these terms can be summarized in the following way:

- As claimed by the theory of social control, the composition of the network varies the effectiveness and quality of informal social controls;
- As claimed by the differential association theory, honest/damaging behaviours are learned through interactions with an agent's context of origin. This justifies the importance given in the model to the number of connections that link an agent to the other members of its network: more interactions = more learning.

2.2 Simulation 1: Effects of punishment on other-damaging behaviours

Imagine a society of 200 agents which live for a fixed length of time and are then replaced by a second generation of 200 agents, and so on for a certain number of generations. The agents of each generation learn how to behave from the agents of the preceding generation. Each agent can exhibit one of two possible behaviours: it can exhibit a behaviour which does not damage other agents ("honest", "H" behaviour) or it can exhibit a behaviour that damages another randomly selected agent ("dishonest", "DH" behaviour). Each agent has one number associated with it which describes the probability that the agent will behave dishonestly and, if an agent does not behave dishonestly, it will behave honestly. For example, if an agent has an associated number of 64, in each time cycle of its life the agent will have a 64% probability of behaving dishonestly and a 36% probability of behaving honestly. We call the agents that have a greater probability of acting dishonestly "dishonest agents" ("DH agents") while we call the agents that have a greater probability to act honestly "honest agents" ("H agents"). A DH agent will generally act dishonestly but, since we are talking about probabilities, in some more or less rare occasions a DH agent may act honestly and an H agent dishonestly.

Each agent has associated with it a level of well-being and the agent's level of well-being changes with the behaviours exhibited by the agent and with the behaviour of other agents. Honest behaviour increases by some quantity the level of well-being of the agent that behaves honestly without changing the level of well-being of other agents. Dishonest behaviour also increases by some quantity the level of well-being of the agent that behaves dishonestly but, in addition, it decreases by the same quantity the level of well-being of another randomly selected agent. Dishonest behaviour can be punished with some probability, where punishment means that the level of well-being of the agent which exhibits dishonest behaviour is decreased by some quantity. These quantities and the probability of punishment for dishonest behaviour are all parameters that are varied in different simulations.

What determines the probability of honest or dishonest behaviour on the part of any particular agent? At the beginning of the simulation the number associated with each agent is chosen randomly with the only restriction that half of the agents are honest and half dishonest (100 and 100). All agents live for the same number of cycles and in each cycle an agent exhibits either an honest or a dishonest behaviour according to the number (probability) associated with the agent, and its level of well-being is changed in accordance with this behaviour. At the end of their life the agents are replaced by a second generation of agents with the same total number of members as the first generation (200). The agents of the second generation learn how to behave from the agents of the first generation. Each agent of the second generation "inherits" the number associated with its "model" (probability of exhibiting dishonest behaviour) with some random variation which may either increase or decrease the number. Hence, each agent of the second generation will behave more or less in the same way as the agent of the first generation chosen as its "model". (One limitation of our simulations is that, by assuming that the individuals of one generation have the same length of life and are simultaneously replaced by the individuals of the next generation, there is no generational overlap which, in actual reality, may play an important role in learning from others.)

What is crucial is that the "models" to be imitated are chosen as a function of their level of well-being, with the agents that have a higher level of well-being (as a result of their behaviour) being more likely to be chosen as "models" by the agents of the second generation. As we have already said, each generation is made of 200 agents. The best 50 agents of each generation are chosen as "models" to be imitated and each "model" is imitated by 2 agents of the next generation. (These values have been chosen arbitrarily and they can have an influence on the results of the simulations.) Therefore, while the first generation of agents includes 100 honest and 100 dishonest agents, these numbers can change in the succession of generations of agents. The simulation goes on for 30 generations and at the end we determine what is the number of DH agents in the society.

Before we describe the results of our simulations we want to comment on the meaning of their parameters, that is, on the aspects of social reality that the simulation parameters try to capture (of course, in a hugely simplified way).

a) Payoff of honest behaviour
The parameter of the increase in one's level of well-being that can be obtained with honest behaviour (payoff of honest behaviour) refers to how much can be gained by living an honest life, i.e., how easy is to find an honest occupation and what is the level of well-being that can reached by working "honestly" (through salaries, wages, profits, buying and selling goods, etc.). In practice, we define as "honest" any behaviour that does not damage others.

b) Payoff of dishonest behaviour
The parameter of the increase in one's level of well-being that can be obtained with dishonest behaviour (payoff of dishonest behaviour) refers to how much can be gained from dishonest behaviour, i.e., how much one's level of well-being can be increased by engaging in behaviours that damage others.

c) Severity of punishment

The parameter of the quantity of punishment which is received if one behaves dishonestly refers to how severe are the written laws of the State. In our simulations punishment can be fair, severe, or lax, where “fair” means that, when it gets punished, a DH agent loses the same quantity of resources which it has obtained with its dishonest behaviour, while “severe” and “lax” mean that the DH agent loses twice or half, respectively, the quantity of resources obtained with its dishonest behaviour. The role of this parameter can be better understood if we add another parameter to the simulation. In addition to specifying the probability of dishonest behaviour on the part of the agent, the characteristics of an agent may also specify the amount of damage caused in another agent if the agent behaves dishonestly, with a corresponding variation in the quantity of resources obtained by the damaging agent with its dishonest behaviour. In other words, a DH agent can “decide” the amount of resources subtracted to the damaged agent, and if the agent becomes a “model” for the agents of the next generation it will teach them to reduce the well-being of the damaged agent by the same quantity (with some random variation of this quantity). If we add this new parameter to our simulations, we can study two other phenomena: what are the consequences of severity of punishment and of punishment commensurate to the gravity of “crimes”, and how the variation of the other parameters influences the gravity of the “crimes” committed by DH agents.

d) Probability of punishment
Finally, the parameter of the probability that a dishonest behaviour is punished refers to how probable is that dishonest behaviour is discovered and punished by the state. As we have said, in real societies there may be many different factors that determine the probability that dishonest behaviours will be discovered and punished: the effectiveness of the punishing system, the nature of the crime (against specific individuals or against the entire community), the existence of organized crime, etc. All these factors are summarized by the parameter of probability of punishment.

2.2.1 Experiment n. 1

In one first group of simulations DH agents do not decide the quantity of damage inflicted with their dishonest behaviour, and therefore the quantity of resources they obtain with this behaviour, but the value of this parameter is decided by us.

Societies tend to invest in punishing DH agents in order to contain dishonest behaviour but the level of investment can vary, and this variable investment results in different probabilities that DH agents will be punished. In our simulations we have varied the probability that DH agents are punished from 1% (very little investment: DH agents are almost never punished), to 5% (little investment: DH agents are rarely punished), 50% (somewhat more investment: DH agents are punished half of the time), and 100% (full investment: DH agents are always punished). We have examined the consequences of level of investment in punishing DH agents in three types of societies:

a) societies in which the payoff of dishonest behaviour is twice or three times as great as the payoff of honest behaviour (2 or 3 units vs. 1 unit);

b) societies in which the payoff of dishonest behaviour is the same as the payoff of honest behaviour (1 unit of additional resources gained with both honest and dishonest behaviour);

c) societies in which the payoff of dishonest behaviour is only half as great as the payoff of honest behaviour (1 unit vs. 2 units).

Another variable that we have manipulated is severity of punishment. Punishment of dishonest behaviour can be fair, i.e., identical to the damage inflicted to the other agent and therefore to the payoff for dishonest behaviour (for example, 1 unit of damage, 1 unit of punishment) or it can be severe (1 unit of damage, 2 units of punishment) or lax (1 unit of damage, half unit of punishment).

The results of the simulations show (Figure 2) that, in a society in which the payoff of dishonest behaviour is twice as great as the payoff of honest behaviour (2 units vs. 1 unit), DH agents (almost) disappear from the society only if the level of investment of the state in punishing DH agents is so high that DH agents are always punished (100% probability). Even if probability of punishment is 100% but severity of punishment is low (half the payoff for dishonest behaviour, i.e., 1 unit), at the end of the simulation DH agents are still somewhat more numerous than H agents. If the level of investment is lower so that DH agents are punished with only a probability of 50%, DH agents disappear only if punishment is severe (twice the payoff for dishonest behaviour, i.e., 4 units). If punishment is commensurate to the payoff of dishonest behaviour (2 units), DH agents continue to constitute half of the society as at the beginning of the simulation. And if level of investment in punishing DH agents is even lower so that DH agents are rarely punished (probability of being punished of 5% or 1%), DH agents colonize the entire society, that is, all agents become DH agents.

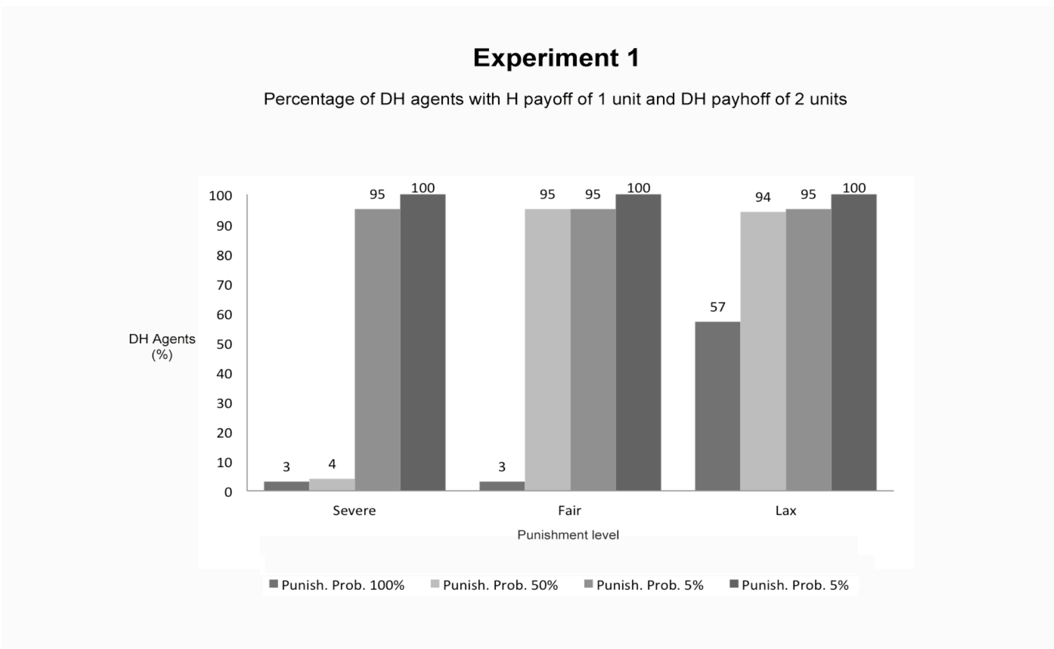

Fig. 2

Of course, containing dishonest behaviours is even more difficult if the payoff of dishonest behaviour is three times as great as the payoff of honest behaviour. DH agents disappear only if the investment in punishing them is at maximum level (100% probability of punishing DH agents) and punishment is fair or severe, or if probability of punishing DH agents is 50% but punishment is severe. In all other types of societies, DH agents again colonize the entire society.

We now turn to societies in which the payoffs of honest and dishonest behaviours are the same (1 unit). In these societies (figure 3) DH agents disappear only if level of investment on the part of the society in punishing dishonest behaviour is great enough so that DH agents are punished with a probability of 100% or 50%. However, if the probability is only 5%, DH agents are almost completely eliminated only if punishment is severe (2 units), while a small minority of DH agents remain if it is fair or lax. If probability of punishment is lower (1%), this minority of DH agents is somewhat greater.

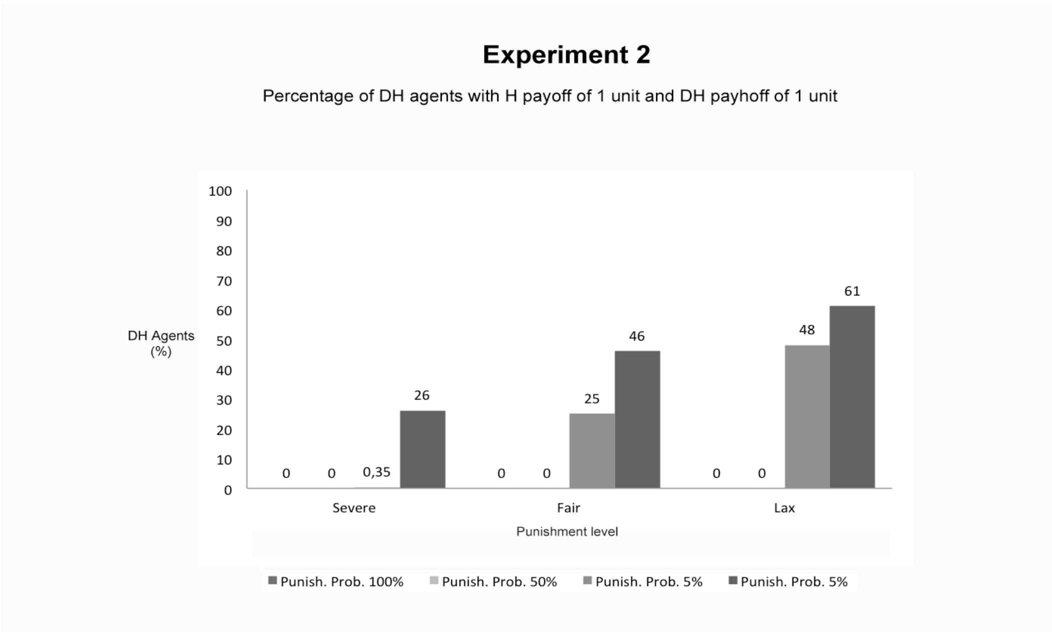

Fig. 3

Finally, in the third type of society in which the payoff of honest behaviour is greater than the payoff of dishonest behaviour, i.e., 2 units for honest behaviour vs. 1 unit for dishonest behaviour, DH agents are eliminated whatever the level of investment in punishing them (even with 1% probability of punishing them) and whatever the severity of punishment (even with lax punishment).

2.2.2 Experiment n. 2

In the simulations we have described DH agents do not decide the payoff of their dishonest behaviour but this payoff is decided by us. This is not very realistic since dishonest behaviour may vary with respect to its payoff for the DH agent and therefore to the quantity of damage caused in another agent (more or less serious crimes). In a second group of simulations we have given DH agents the freedom to “choose” the seriousness of the damage caused in another agent and therefore the payoff of their dishonest behaviour. (Remember that in all our simulations the payoff of other-damaging behaviours is identical to the damage caused by these behaviours.) We have associated to each agent another number that specifies the extent of the damage caused in another agent by the dishonest agent's behaviour. This number also is learned by the agents from their "model", with some random variation that can slightly increase or decrease its value. Unlike the preceding simulations, in these new simulations DH agents can be different from one another in the quantity of damage inflicted to another agent with their dishonest behaviour, and therefore in their payoff, and the average quantity of damage inflicted to others with dishonest behaviour can change from one generation to the next. In the first generation all agents are assigned a number randomly selected between 1 and 10 (of course this number becomes effective only for agents behaving dishonestly.)

We have run three sets of simulations by varying the payoff of honest behaviour from 1 to 2 to 5 units, and for each set we have varied the other two parameters, i.e., probability of punishment and severity of punishment, in the same way as in the simulations with a fixed payoff for DH agents.

When the payoff for honest behaviour is small, i.e., 1 unit, the results are similar to those obtained with a payoff of honest behaviour of 1 unit and a payoff of dishonest behaviour of 3 units. DH agents are eliminated from the society only when the probability of punishment for dishonest behaviour is 100% and the level of punishment is fair or severe or when probability of punishment is 50% and the level of punishment is severe (cf. the preceding simulations). This also happens if the payoff for honest behaviour is somewhat higher, that is, 2 units. On the other hand if the payoff for honest behaviour is significantly higher, i.e., 5 units, we return to the situation of the preceding simulations in which the payoff for honest behaviour was 2 units and that for dishonest behaviour was 1 unit. In all circumstances, i.e., with all probabilities of punishment and with all levels of punishment, DH agents are eliminated from the society.

If we look at the average quantity of damage inflicted to other agents by DH agents in the various simulations, we find the following. In the simulations with 1 or 2 units of payoff for honest behaviour, when DH agents colonize the entire society the quantity of damage caused in other agents and therefore their payoff is very high. In contrast, in the simulations in which DH agents are eliminated from society (that is, when probability of punishment is 100% and level of punishment is fair or severe or when probability of punishment is 50% and level of punishment is severe), the average quantity of damage inflicted by DH agents is medium or low. When the payoff for honest behaviour is higher, i.e., 5 units, so that DH agents are eliminated from the society for all levels of probability of punishment and for all levels of punishment, DH agents tend to disappear but until they disappear they tend to commit serious crimes if probability of punishment is low and somewhat less serious crimes only if the probability of punishment is very high (100%) and the level of punishment is severe.

2.3 Simulation 2: introducing sub communities and learning dynamics

In Simulation 1 a society is a set of individuals and, when an individual damages another individual, the damaged individual is chosen randomly. But societies are not just sets of individuals. They are networks of nodes where a node is an individual and a connection between two nodes indicates that the individuals represented by the nodes interact with each other. A network has a topology that specifies who interacts with whom. The topology may not be homogeneous but there may be sub-networks of more densely interconnected nodes which are more sparsely connected with other sub-networks. What are the consequences of this property of societies for the ability of the state to contain other-damaging behaviours?

2.3.1 Experiment n. 3

In the simulations we have already described, the only interactions among the agents take place when an agent learns whether to behave honestly or dishonestly by imitating an agent of the preceding generation. In the new simulations (experiment n. 3, see figures 5 and 6), in addition to this type of learning there is a second type of learning: an agent also learns how to behave by imitating the agents with which it interacts during its life. This implies that the honesty or dishonesty of an agent may not remain identical for the entire life of the agent but it may change because of the social interactions of the agent with other agents.

There are two differences between learning by imitating an individual of the preceding generation and learning by imitating the individuals with whom one interacts during life. The first difference is that an individual chooses the model to imitate among the individuals of the preceding generation on the basis of their well-being while the individual imitates the individuals with which it interacts during its life independently of their well-being. The second difference is that imitation due to social interaction is reciprocal. If two agents are connected together, each agent will tend to adopt the type of behaviour, honest or dishonest, of the other agent. Notice that since societies are networks of nodes that may include more densely interconnected sub-networks, this second type of learning will take place mainly within these sub-networks of nodes.

At the beginning of the simulation the agents have an average number of randomly assigned bidirectional connections which is 1.5 in one set of simulations and 5 in another set. During an agent's 100 cycles of life an agent tends to imitate the agents with which it is connected, i.e., to become more honest if it interacts with an honest agent and more dishonest if it interacts with a dishonest agent, and therefore the agent's behaviour may change during its life. The probability that an agent will imitate another agent is 0.01 but we have also tried a smaller probability of 0.001 for a sub-set of the simulations. In all other respects the new simulations are identical to the simulations already described. An agent has a certain inherited level of well-being and this level is changed by the agent's behaviour, honest or dishonest, by the behaviour of other (dishonest) agents, and by the action of the state which, with some probability and with more or less severity, punishes, i.e., reduces the quantity of resources of, the agents which act dishonestly. At the end of life each agent has a certain level of well-being and the agents with the highest level of well-being are selected as “models” by the agents of the next generation. The simulation goes on for 30 generations.

What determines the structure of the network of nodes (agents)? As we have said, at the beginning of the simulation, the connections between pairs of nodes are randomly assigned (figure 4) with the constraint that the average number of connections per node has to be 1.5 or 5 in two distinct sets of simulations, and this constraint remains throughout the simulation. However, the topology of the connections changes in the successive generations of the simulation. When an agent is selected as a “model” to be imitated by two agents of the next generation, the two “imitator” agents are necessarily connected together. Hence, they will act similarly, either honestly or dishonestly, not only because they are both “imitators” of the same agent of the preceding generation but also because they imitate each other. This tends to create sub-communities (sub-networks) of agents that act in the same way.

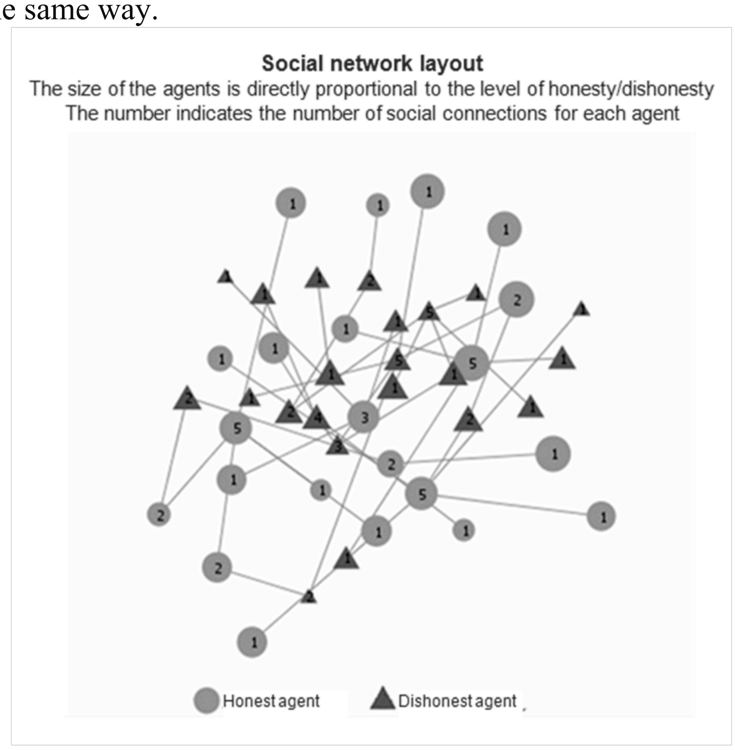

figure 4

The results of the simulations indicate that the presence of sub-communities of similar agents creates a new obstacle to the action of the state aimed at containing other-damaging behaviours. The variables whose role we have explored in the preceding simulations still play a role in determining the percentage of dishonest agents in the society. As in the preceding simulations, this percentage increases with a decreasing probability of being punished and with a decreasing severity of punishment but the main variable that determines the percentage of dishonest agents in the society is the payoff of honest vs. dishonest behaviour. However, in all conditions the existence of social imitation during life increases the percentage of dishonest agents, and this increase is greater when the average number of links is 5 (figure 5 and 6) rather than 1.5, that is, when there are more opportunities to interact with other agents.

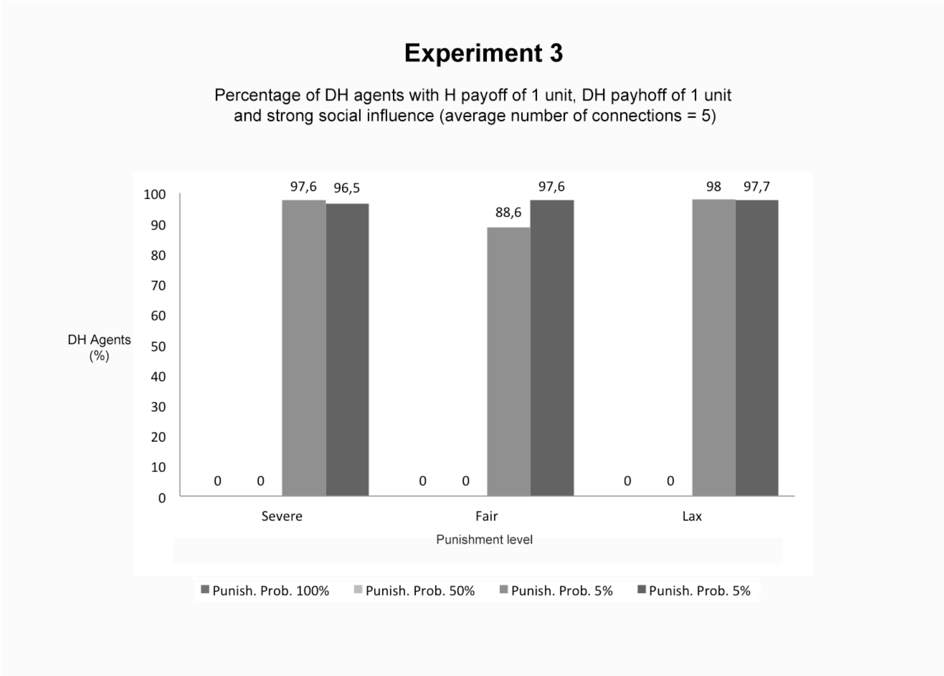

Fig. 5

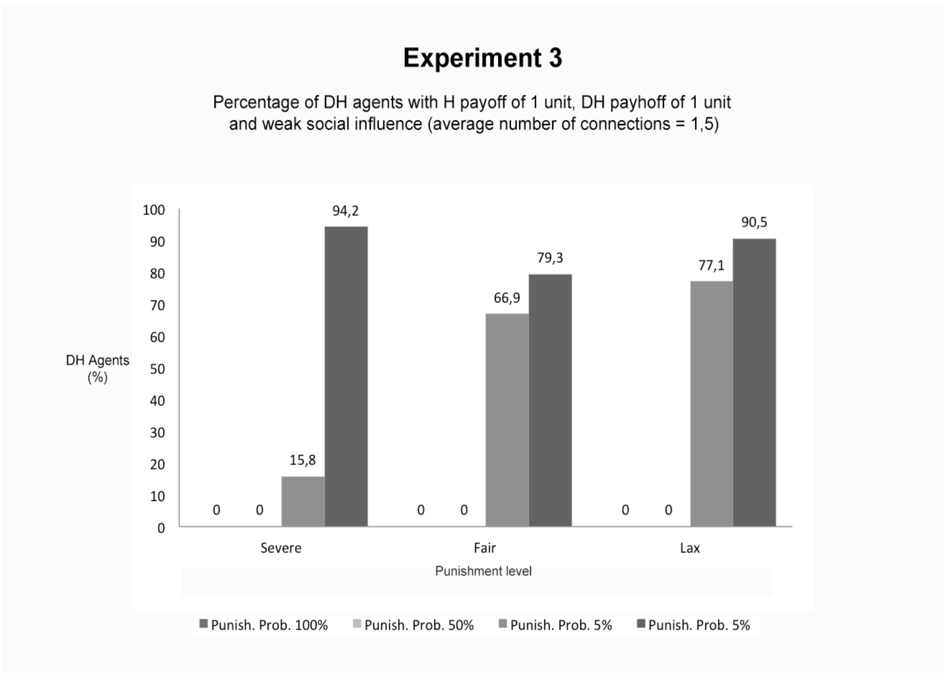

Fig. 6

3. Discussion

In this paper we have used a simple evolutionary simulation to explore the dynamics of a phenomenon that belongs to an area of social issues (the social impact of punishment and sanction) often investigated through models in which agent are endowed with complex cognitive architectures (Savarimuthu and

Cranefield 2009; Neumann 2010). In our model, the only concepts that appear to be necessary to analyse the phenomena are the concepts of other-damaging behaviour, i.e., behaviour that reduces the well-being of other individuals or of the entire community, and punishment, interpreted as the behaviour of an individual or a central structure which causes a reduction in the well-being of the individual who has exhibited other-damaging behaviours and therefore makes these behaviour less probable in the future. In our simulations we have manipulated a number of variables and we have tried to show how these variables influence the capacity of the mechanism to contain other-damaging behaviours.

The results of our simulations suggest that the best policy for eliminating dishonest behaviour is not to increase the probability that dishonest behaviours will be punished or to increase the severity of punishment but to create opportunities for the members of the society to live well with honest behaviour. Only if this strategy is adopted, DH agents are almost completely eliminated from the society, independently of the probability of punishing them and of the severity of punishment. On the contrary, if the payoff of dishonest behaviour is as great as or greater than that of honest behaviour, it is possible to eliminate dishonest behaviour only if there is a very high probability of discovering and punishing dishonest behaviours. The tentative conclusion that can be drawn from our simulations is that the best strategy for containing other-damaging behaviours is for the state to invest so as to increase the payoff of honest behaviours, and this conclusion is in accordance with Merton's (1949) idea that individuals tend to behave criminally when the society does not provide them with the possibility to realize their aspirations by behaving honestly. However, based on empirical data whether the state should invest in "jobs or jails" remains an open question (see, e.g., Spelman 2005).

However, both investing in discovering and punishing other-damaging behaviours and investing in creating the conditions for the non-emergence of other-damaging behaviours are strategies that require the employment of significant economic resources on the part of the state. The problem here is the problem of all types of spending on the part of the state: the state may not have sufficient resources (obtained through the fiscal system) to spend so that the mechanism for discovering and punishing other-damaging behaviours may function with the required high level of effectiveness or the average agent can get a sufficiently high payoff from honest behaviour.

Another problem for the state is that there may be sub-communities of interacting dishonest individuals ("criminal sub-cultures") which, as shown by the results of our second set of simulations, can reduce the efficacy of the action of the state aimed at containing other-damaging behaviours. Today this problem may be more serious because while traditional criminal sub-cultures tended to be territorial, that is, they were restricted to specific geographical regions, advances in the technologies of information and communication make it possible for people to interact independently of the physical location of the interacting individuals, and this offers new opportunities for criminal sub-cultures to expand globally.

The second set of simulations shows the importance of cultural factors in determining whether an individual will behave honestly or dishonestly. This is in contrast with a view of social behaviour as based on the individual's rational choices and it is in accordance with Durkheim's idea that the characteristics of the social environment impose themselves to the individual with or without the individual's acceptance (Durkheim 1964; Matza and Sykes 1961). Other links can be found with the idea that the attachment of an individual to the other members of the his/her group will lead the individual to behave like them, and with the differential association theory (Sutherland 1937; 1947; Hirschi 1969) according to which criminal behaviour is learnable and learned in interaction with other persons. This is also linked to various theories of social control (Durkheim 1964; Sampson and Laub 1993; Sampson 2006).

The general conclusion that can be drawn from our simulations is that if the only mechanism for containing other-damaging behaviour is the system of legal sanctions which is implemented by the state, it is very difficult to avoid that other-damaging behaviours exist and are widespread in the society. Other-damaging behaviours can be more easily eliminated if the state invests enough resources to make the probability of punishment for dishonest behaviour very high or to increase the payoff of honest behaviour for the average citizen or in other positive ways and, as we have said, this is not very realistic for purely economic reasons. In addition, as Cesare Beccaria already observed more than two centuries ago (Beccaria 2009) and as many recent studies have confirmed (e.g., Akers and Sellers 2004), our simulations suggest that the level of severity of punishment does not play a significant role as a strategy for containing other-damaging behaviour. Other factors which tend to decrease the effectiveness of the action of the state aimed at containing other-damaging behaviours are the particular difficulty of discovering and punishing behaviours that damage the entire community rather than specific individuals and the existence of criminal sub-cultures which today are greatly helped by globalization.

The simulations described in this paper address in a very simplified form the relations among some of the variables that play a role in determining the effectiveness of the action of the state aimed at containing other-damaging behaviours. We plan to develop these simulations in order to address other phenomena such as the differences among different categories of other-damaging behaviours, and in particular between behaviours that damage specific individuals and behaviours that damage the entire community, the existence of criminal organizations, and not only criminal cultures, and how globalization may affect other-damaging behaviours and their containment. If we interpret the results of the simulations as the predictions derived from the model incorporated in the simulations, these predictions should be verified with various classes of empirical data such as data on the different types of criminal behaviours and on the geographical distribution of criminal behaviours.

4. Conclusions

We want to conclude by briefly sketching some considerations about the actual and the future role of simulation models in dealing with policy making issues. The study of methodologies and tools for policy/rule making is one of the most interesting legal research field that can take advantage from computer simulations and, more in general, from research methodologies belonging to the area of computational social sciences (Lettieri and Faro 2012).

As recently remarked (Troitzsch 2013), actual and possible applications of simulation models to support policy making and legislation have shown that simulations have a large but still not really exploited potential of giving legislators insights into the possible consequences or their actions. Nevertheless, all kinds of simulation are and probably for a long time will be unable to make precise predictions about the outcomes of planned policies, even if probabilities can be given for the alternative paths. What is only possible is a foresight in the sense that possible futures can be sketchily described. The responsibility for the measures taken by policy makers remains with policy makers even if simulation can improve the information on which political decisions rest.

In this context, the road ahead is full of challenges from a scientific, methodological and technical point of view. A crucial issue seems to be the design of more empirically grounded models: the predictive power of simulation can probably take advantage of more realistic models (Cioffi-Revilla 2010b). This choice leads to a significant priority for simulation design: strengthen the connection between the model and real data concerning the phenomena under investigation. Therefore, "the search for strategies to find and extract data from reality, and integrate agent-based models with other traditional empirical social science methods, such as qualitative, quantitative, experimental and participatory methods, becomes a fundamental step of the modelling process" (Boero and Squazzoni 2005). The consequences are essentially two: the need for an increasingly interdisciplinary approach to the investigation of social phenomena and the use of different and more powerful tools in order to realize more realistic and complex simulations. Anyhow, simulations like the one we present in this paper, notwithstanding their extreme simplicity and exploratory nature, can still provide ideas for designing new policies offering an operational way to deal with social problem as a tool for rapid prototyping and theory making.

As to legal science in particular, we think that simulations are offering a great opportunity to deepen the understanding of the empirical dimension (cognitive, social, economic) of phenomena that are relevant for law and that are ruled by law (Edmonds 2013). A critical step in this prospect is the choice for a open approach to the analysis of legal issues and the opening towards research methods that often do not belong to the traditional horizons of legal scientist. From this point of view, it will be essential to overcome division between disciplines defined largely by methodology and to consider social sciences as a field through which various pathways are possible. The perspective of a methodological pluralism, more and more diffused in the area of social sciences (Della Porta and Keating 2008), represents in this respect an interesting reference, a promising starting point.

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