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Exploring the Effects of Sanctions on Damaging Actions through Artificial Societies: A Simulation Model

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1. INTRODUCTION

After the invention of electronic computers, the role played by computational techniques in social sciences (here defined in a broad sense as the complex 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[1], a "fledging interdisciplinary field at the intersection of the social sciences, computational science, and complexity science"[2], is gradually changing the way in which social phenomena are investigated and managed. The set of computational social science methods is wide and encompasses differents techniques: automated information extraction; social network analysis;

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[1] D. LAZER *et al.*, *Computational Social Science*, in "Science", Vol. 323, 2009, n. 5915, pp. 721-723.

[2] C. CIOFFI-REVILLA, *Computational Social Science*, in "Wiley Interdisciplinary Reviews: Computational Statistics", Vol. 2, 2010, n. 3, pp. 259-271; see also ID., *Scienza sociale computazionale e scienza giuridica*, in Faro S., Lettieri N., Tartaglia Polcini A. (a cura di), "Diritto e tecnologie: verso le scienze sociali computazionali. Attualità e orizzonti dell'Informatica giuridica", Napoli, ESI, pp. 205-227.

geospatial 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[3] 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[4]. 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"[5]. Based on the identification of the scientific explanation with the reproduction *in silico* (i.e. in a computer simulation), of 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[6]. 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, In ABM researchers model agents as distinct parts of a computer program that may contain heterogeneous variables, parameters, and behaviour. 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.

Epistemological consequences of agent-based modeling are relevant. ABM is establishing the primacy of modelling for social science descriptions and theorizing, in contrast with the prevalent use of narrative descriptions and un-formalized theorizing that dominate (with the exception of economics) most social science discourse[7]. Moreover ABM has strengthened an

[3] R. CONTE, R. HEGSELMANN, P. TERNA (eds.), *Simulating Social Phenomena*, Berlin-Heidelberg, Springer, 1997.

[4] G.M.P. O'HARE, N.R. JENNINGS (eds.), *Foundations of Distributed Artificial Intelligence*, New York, John Wiley & Sons, 1996.

[5] N. GILBERT, *Agent-based Models*, London, Sage Publications, 2007.

[6] J.M. EPSTEIN, *Generative Social Science: Studies in Agent-based Computational Modeling*, Princeton, Princeton University Press, 2006; F. SQUAZZONI, *Epistemological Aspects of Computer Simulation in the Social Sciences*, Berlin-Heidelberg, Springer, 2009.

[7] R. FRANK, *The Explanatory Power of Models. Bridging the Gap between Empirical and Theoretical Research in the Social Sciences*, Dordrecht, Kluwer Academic Publishers, 2002.

"issue-oriented" style of research that is "favouring trans-disciplinary collaboration and stepping over the classic social science disciplinary boundaries"[8]. According to this approach, a growing community of social scientists investigates topics spanning from cooperation[9] to reputation[10], from the emergence of conventions[11] to the evolution of institutions[12] and the emergence of norms[13], 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[14].

[8] F. SQUAZZONI, *The Impact of Agent-based Models in the Social Sciences after 15 Years of Incursions*, in "History of Economic Ideas", Vol. 18, 2010, n. 2, pp. 197-233.

[9] R. AXELROD, *The Complexity of Cooperation. Agent-based Models of Competition and Collaboration*, Princeton, Princeton University Press, 1997.

[10] R. CONTE, M. PAOLUCCI, *Reputation in Artificial Societies: Social Beliefs for Social Order*, Dordrecht, Kluwer, 2002.

[11] G.M. HODGSON, T. KNUDSEN, *The Complex Evolution of a Simplex Traffic Convention. The Function and Implications of Habits*, in "Journal of Economic Behavior and Organization", n. 54, 2004, pp. 19-47; J. CARPENTER, *Evolutionary Models of Bargaining: Comparing Agent-based Computational and Analytical Approaches to Understanding Convention Evolution*, in "Computational Economics", Vol. 19, 2002, n. 1, pp. 25-49.

[12] C. CIOFFI-REVILLA, S. LUKE, D.C. PARKER, J.D. ROGERS, W.W. FITZUGH, W. HONEYCHURCH, B. FROHLICH, P. DE PRIEST, C. AMARTUVHIN, *Agent-based Modeling Simulation of Social Adaptation and Long-term Change in Inner Asia*, in Terano T., Sallach D. (eds.), "Advancing Social Simulation: The First World Congress in Social Simulation", Berlin, Springer Verlag, 2007.

[13] R. CONTE, C. CASTELFRANCHI, *Understanding the Functions of Norms in Social Groups through Simulation*, in Gilbert N., Conte R. (eds.), "Artificial Societies. The Computer Simulation of Social Life", London, UCL Press, 1995, pp. 252-267; M.J. EPSTEIN, *Learning to Be Thoughtless: Social Norms and Individual Competition*, in "Computational Economics", Vol. 18, 2001, pp. 9-24; R. CONTE, R. FALCONE, *ICMAS '96: Norms, Obligations, and Conventions*, in "AI Magazine", Vol. 18, 1997, n. 4, pp. 145-147.

[14] S. MOSS, *Policy Analysis from First Principles*, in "Proceedings of the National Academy of Sciences of the United States of America", Vol. 99, 2002, n. 3, pp. 7267-7274; F. SQUAZZONI, R. BOERO, *Complexity-friendly Policy Modelling*, in Ahrweiler P. (ed.), *Innovation in Complex Social Systems*, London, Routledge, 2010, pp. 290-299.

Even if belonging to the area of social sciences, legal science has substantially fallen behind in the research about agent-based models. Yet, as we will highligth below, there are various reasons for legal scientist to look at ABM: not only, in general terms, because they can contribute to illumitate social dynamics that are relevant for law but also, more specifically, because legal issues and procedures (norm making, regulatory impact analysis) are important parts of policy making ABM may support. It is therefore important to promote in 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 simulation 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. The Target Phenomenon: Other-damaging Behaviours

In order to show the potential of ABM, we propose a simulation model of a wide class of human behaviours that we define "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. As noted by Hoebel[15], "social norms are mental constructs" but we prefer to avoid mental constructs and to choose a more operational approach that postulates only more directly observable entities and processes. Social norms[16], with the exception of written laws and regulations, cannot be directly observed and therefore we prefer not to use the notion of social norm. Furthermore, there is a "variety of concepts of norms"[17] and, instead of defending our own definition, we try to more directly capture with our model the empirical phenomena that the concept is intended to explain.

[15] A.E. Hoebel, *The Law of Primitive Man. A Study in Comparative Legal Dynamics*, Harvard, Athaeneum, 1954.

[16] M. Hechter, K.D. Opp (eds.), *Social Norms*, New York, Sage, 2001.

[17] M. Neumann, *Homo Socionicus: A Case Study of Simulation Models of Norms*, in "Journal of Artificial Societies and Social Simulation", Vol. 11, 2008, n. 4, http://jasss.soc.surrey.ac.uk/11/4/6.html; M. Neumann, *Norm Internalisation in Human and Artificial Intelligence*, in "Journal of Artificial Societies and Social Simulation", Vol. 13, 2010, n. 1, http://jasss.soc.surrey.ac.uk/13/1/12.html.

The concepts in terms of which we will analyse the phenomena we are talking about are "other-damaging behaviour" and "social punishment". "Other-damaging behaviours" are behaviours that reduce the well-being of specific other individuals or of the entire community. "Social punishment" is any behaviour on the part of other individuals or of some central authority that decreases the probability that an individual will exhibit other-damaging behaviours in the future.

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 exchange 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[18]. 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 diffuse 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. Furthermore, many different disciplines study

[18] D. PARISI, *What to Do with a Surplus?*, in Conte R., Hegselmann P., Terna P. (eds.), "Simulating Social Phenomena", New York, Springer, 1997, pp. 133-151.

other-damaging behaviours and the different mechanisms used by societies to contain these behaviours, from psychology to anthropology, from sociology to political science, from history to legal science and criminology.

Legal scientists should especially be concerned with the dynamics discussed in this paper, at least the ones inspired by those schools of thought that are interested in the empirical aspects of legal phenomena and try to approach them with and interdisciplinary orientation, such as Legal Realism[19] and Institutionalism[20]. Legal science, on the other hand, should not be interpreted only as the exegesis of written norms or the definition and systematization of abstract legal concepts, but also as the analysis of the empirical processes which underlie legal phenomena. In this prospect agent-based models, with their ability to support the understanding of social and economic dynamics seem able to help devising more effective legal systems in that social and economic factors can increase or reduce the effectiveness of laws and regulations[21].

The idea of using computational artifacts for the investigation of socio-legal phenomena dates back to the '40s of the last century[22] and computer simulations have been described as a viable tool for legal analysis[23] and for the study of empirical phenomena linked to the functioning of legal systems and institutions[24], and, especially, in the more empirically oriented disci-

[19] K. LLEWELLYN, *Jurisprudence. Realism in Theory and Practice*, Chicago, Chicago University Press, 1962.

[20] M. HAURIOU, *Aux sources du droit: le pouvoir, l'ordre, et la liberté*, Paris, Bloud & Gay, 1933; N. MC CORMICK, O. WEINBERGER, *An Institutional Theory of Law*, Dordrecht, D. Reidel, 1986; M. LA TORRE, *Institutionalism Old and New*, in "Ratio Juris", Vol. 6, 1993, pp. 190-201.

[21] E.A. POSNER, *Law and Social Norms*, Cambridge, Harvard University Press, 2000; B.Z. TAMANAHA, *A General Jurisprudence of Law and Society*, Oxford, Oxford University Press, 2001.

[22] L. LOEVINGER, *Jurimetrics*, in "Minnesota Law Review", Vol. 33, 1949, pp. 455-493; H.W. BAADE (ed.), *Jurimetrics*, New York, Basic Books, 1963.

[23] D.A. DEGNAN, C.M. HAAR, *Computer Simulation in Urban Legal Studies*, in "Journal of Legal Education", Vol. 23, 1970, pp. 353-365; J. DROBAK, *Computer Simulation and Gaming: An Interdisciplinary Survey with a View Toward Legal Applications*, in "Stanford Law Review", Vol. 24, 1972, n. 4, pp. 712-729; M. AIKENHEAD, R. WIDDISON, T. ALLEN, *Exploring Law through Computer Simulation*, in "International Journal of Law and Information Technology", Vol. 7, 1999, n. 3, pp. 191-217.

[24] P. VAN BAAL, *Computer Simulations of Criminal Deterrence: From Public Policy to Local Interaction to Individual Behaviour*, Den Haag, Boom Juridische Uitgevers, 2004; T. BOSSE, C. GERRITSEN, *Social Simulation and Analysis of the Dynamics of Criminal Hot Spots*, in

pline of criminology. However, agent-based models still appear to be outside the cultural horizon of most legal scientists.

3. Three Mechanisms for Containing Other-damaging Behaviours

As we have said, to stay together all communities of individuals have to implement some mechanism for containing other-damaging behaviours. Very schematically we distinguish, in this paper, three such mechanisms. All three mechanisms involve some punishment of the individual that has damaged others, that is, some consequences for the individual which, by causing some kind of loss or affliction, will reduce the probability that the individual will exhibit the damaging behaviour in the future. However, the three mechanisms operate at different levels: at the State or institutional level, at the social level and at the individual level.

a) *State level*. The first mechanism for containing other-damaging behaviours is a central structure which is part of the State and which has the task to identify the behaviours that damage other individuals or the entire community and to punish these behaviours according to explicitly formulated laws and regulations. This central structure includes police, investigative bodies, and the judiciary system. The central structure relies on statements (laws and regulations) that specify the different types of other-damaging behaviours and the nature and quantity of punishment to be administered for each different type. Laws and regulations can specify behaviours that *should not be exhibited* or behaviours that *must be exhibited*, and violations of laws and regulations are punished in both cases. The central structure is implemented by specialized organizations that have the task to detect other-damaging behaviours, to classify these behaviours according to the written laws and regulations and previous similar cases, and to decide and administer the appropriate punishment. If we interpret the state as a central store of resources for the community, the existence and appropriate functioning of this central structure is one of the most important resources provided by the State to the community.

"Journal of Artificial Societies and Social Simulation", Vol. 13, 2010, n. 2, http://jasss.soc.surrey.ac.uk/13/2/5.html; L. Liu, J.E. Eck (eds.), *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*, Hershey, IGI Global, 2008.

b) *Social level*. The second mechanism existing in human communities for reducing the probability of occurrence of other-damaging behaviours is the social circulation of information concerning the other-damaging behaviour exhibited by an individual. This socially circulated information induces other individuals to refrain from doing things which benefit the damaging individual and even from interacting with the individual, which is an important type of punishment for such highly social animals as human beings. This second mechanism is called reputation[25] and is an informal one: any individual can contribute to the reputation of any other individual.

c) *Individual level*. The third mechanism consists in the internalization of prohibitions to exhibit other-damaging behaviours which causes psychological pain if the prohibitions are violated or if one even thinks of violating them, and is therefore a form of self-punishment. This third mechanism can be part of a moral education imparted by parents, teachers, and other social authorities, or it can be part of a religious faith or, more generally, of a religious attitude towards reality.

All three mechanisms may obtain the result of limiting the occurrence of other-damaging behaviours not only as a consequence of being actually punished, or self-punished in the case of the third mechanism, but also because human beings can anticipate punishment and this is often sufficient for them to refrain from exhibiting other-damaging behaviours. Furthermore, it is also possible that punishing one individual for his/her other-damaging behaviour will decrease the probability that the other-damaging behaviour will be exhibited not only by the punished individual but by other individuals who are informed that a punishment has taken place.

A community of individuals make recourse to different degrees to the three mechanisms for containing other-damaging behaviours, but if none of them functions adequately, other-damaging behaviours will become common and this may endanger the very existence of the community.

[25] C. CASTELFRANCHI, R. CONTE, M. PAOLUCCI, *Normative Reputation and the Costs of Compliance*, in "Journal of Artificial Societies and Social Simulation", Vol. 1, 1998, n. 3, http://www.soc.surrey.ac.uk/JASSS/1/3/3.html.

4. A Simple Simulation Model of the State-level Mechanism for Containing Other-damaging Behaviours

In this paper we describe some computer simulations (realized using the agent-based modelling environment *Netlogo*[26] and accessible on line at http://goo.gl/yRQ9r) that reproduce the effects of other-damaging behaviours and how a society can try to contain them with the first of the three mechanisms we have distinguished, the mechanism of laws, regulations and sanctions which operates at the State or institutional level. The simulations are extremely simplified and abstract with respect to the actual phenomena but we hope they capture some of the basic underlying principles and can help us to think more clearly about these phenomena. Agent-based simulations should be used not only to explain existing empirical data but also to illuminate the "core dynamics" and to "discover new questions"[27]. Another important advantage of computer simulations is that they make it possible to go beyond disciplinary divisions. As we have said, other-damaging behaviours are studied by a number of distinct disciplines (the disciplines of law, sociology, psychology, etc.) and computer simulations can show how the phenomena studied by these different disciplines work together and influence each other. And, finally, agent-based simulations can be used as tools for evaluating current policies and for designing and evaluating new policies, although one must be aware of the limitations of simple and abstract simulations such as those described in this paper for policy analysis and prediction.

Our simulations are agent-based simulations[28] but our agents are very simple and have very limited interactions. More specifically, our agents are not cognitive agents in the sense that their actions are not determined by the interplay among complex cognitive constructs (i.e. BDI - *Beliefs Desires and Intentions*[29], BOID - *Beliefs, Obligations, Intentions and Desires*) but they can

[26] E. Sklar, *NetLogo, A Multi-agent Simulation Environment*, in "Artificial Life", Vol. 13, 2007, n. 3, pp. 303-311.

[27] J.M. Epstein, *Why Model?*, in "Journal of Artificial Societies and Social Simulation", Vol. 11, 2008, n. 4, http://jasss.soc.surrey.ac.uk/11/4/12.html; T. Grüne-Yanoff, P. Weirich, *Philosophy and Epistemology of Simulation: A Review*, in "Simulation and Gaming", Vol. 41, 2010, n. 1, pp. 20-50.

[28] N. Gilbert, *Agent-based Models*, cit.; J.M. Epstein, *Generative Social Science: Studies in Agent-based Computational Modeling*, cit.

[29] A.S. Rao, M.P. Georgeff, *BDI-agents: From Theory to Practice*, in "Proceedings of the 1st International Conference on Multiagent Systems - ICMAS '95", San Francisco, 1995.

only execute one of two possible actions according to the probabilities of these two actions which are associated with each agent.

Another characteristic of our simulations is that, while the goal of many agent-based simulations is to discover what emerges from the interactions among many agents, the focus of our simulations is on how agents learn to behave as they behave. We use a genetic algorithm[30] to simulate learning, where learning occurs across a succession of generations of agents rather than during an agent's life. We interpret our genetic algorithm not in biological but in cultural terms[31]. 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.

A third characteristic of our model is that while agent-based models tend to be concerned with how cooperation and altruistic behaviour can emerge in populations of selfish individuals[32], our model is concerned with selfish behaviours that damage others – behaviours that increase the well-being of the agent and reduce the well-being of other agents – and with how societies try to contain these behaviours. Our simulations have some similarity to Gary Becker's attempt at explaining criminal behaviour in economic terms[33] but they avoid the complex theoretical apparatus of the science of economics as based on rational choice theory.

[30] M. MITCHELL, *An Introduction to Genetic Algorithms*, Cambridge, MIT Press, 1998.

[31] R. REYNOLDS, *An Introduction to Cultural Algorithms*, in "Proceedings of the 3rd Annual Conference on Evolutionary Programming", Singapore, World Scientific Publishing, 1994.

[32] R. AXELROD, *The Evolution of Cooperation*, New York, Basic Books, 1984; H. GINTIS, S. BOWLES, R.T. BOYD, E. FEHR (eds.), *Moral Sentiments and Material Interests: The Foundation of Cooperation in Economic Life*, Cambridge, MIT Press, 2006; D.B. CORNISH, R.V. CLARKE (eds.), *The Reasoning Criminal: Rational Choice Perspectives on Offending*, New York, Springer, 1986; J. HEINRICH, N. HEINRICH, *Why Humans Cooperate. A Cultural and Evolutionary Explanation*, Oxford, Oxford University Press, 2007; M. TOMASELLO, *Why We Cooperate*, Harvard-Cambridge, MIT Press, 2009.

[33] G.S. BECKER, *Crime and Punishment: An Economic Approach*, in "The Journal of Political Economy", Vol. 76, 1968, pp. 169-217; D.B. CORNISH, R.V. CLARKE (eds.), *The Reasoning Criminal: Rational Choice Perspectives on Offending*, cit.; T. HIRSCHI, *Causes of Delinquency*, Berkeley, University of California Press, 1969.

4.1. Simulation 1: Effects of Punishment

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 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 (for brevity, "honest" behaviour) or it can exhibit a behaviour that damage another randomly selected agent ("dishonest" 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 behave 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, which means that, if punishment occurs, 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 must be 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 it, 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, we have not included a generational overlap in our simulations which 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 and the sanctions 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.

4.1.1. The Quantity of Damage Caused by Dishonest Behaviour Is Fixed

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 (Fig. 1) 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 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.

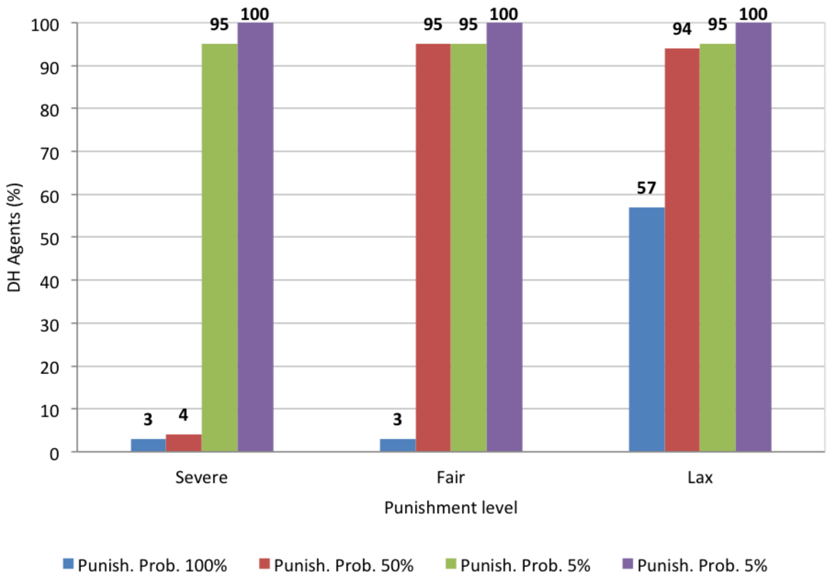

Fig. 1 – Percentage of DH agents with H payoff of 1 unit and DH payoff of 2 units

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 (Fig. 2) 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.

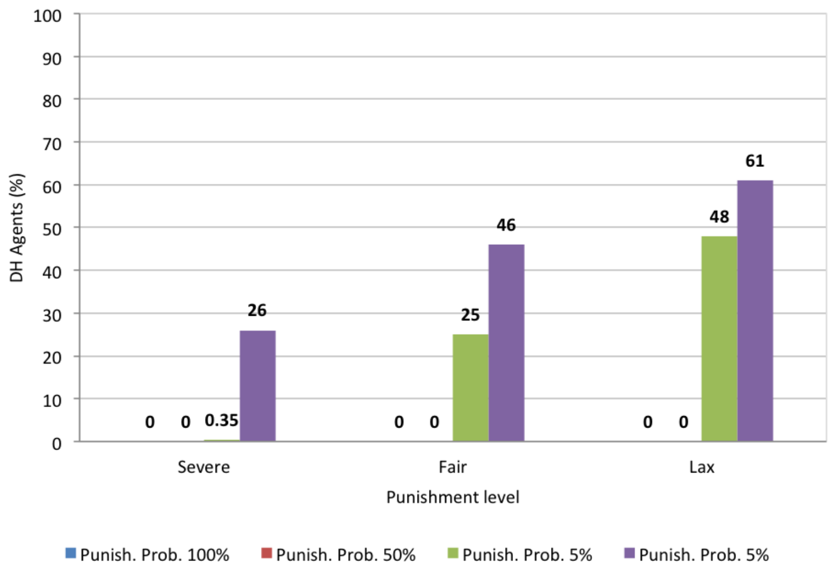

Fig. 2 – Percentage of DH agents with H payoff of 1 unit and DH payoff of 1 unit

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).

4.1.2. DH Agents Vary the Quantity of Resources They Obtain with Their Dishonest Behaviour and Therefore the Quantity of Damage Produced by Their Actions

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. 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.

4.2. Simulation 2: Subcommunities

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 exist 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?

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, 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 subset 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, 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 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.

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 (Fig. 3) rather than 1.5 (Fig. 4), that is, when there are more opportunities to interact with other agents.

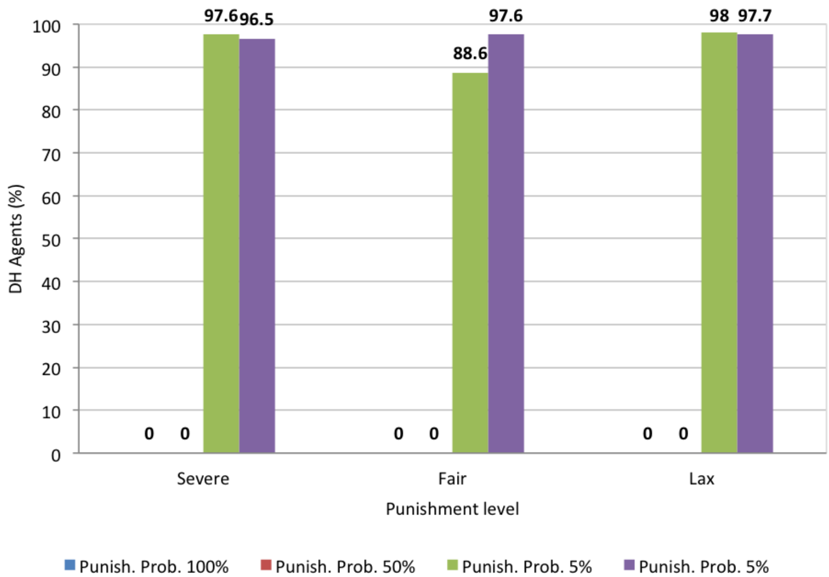

Fig. 3 – Percentage of DH agents with H payoff of 1 unit, DH payoff of 1 unit and strong social influence (average number of connections = 5)

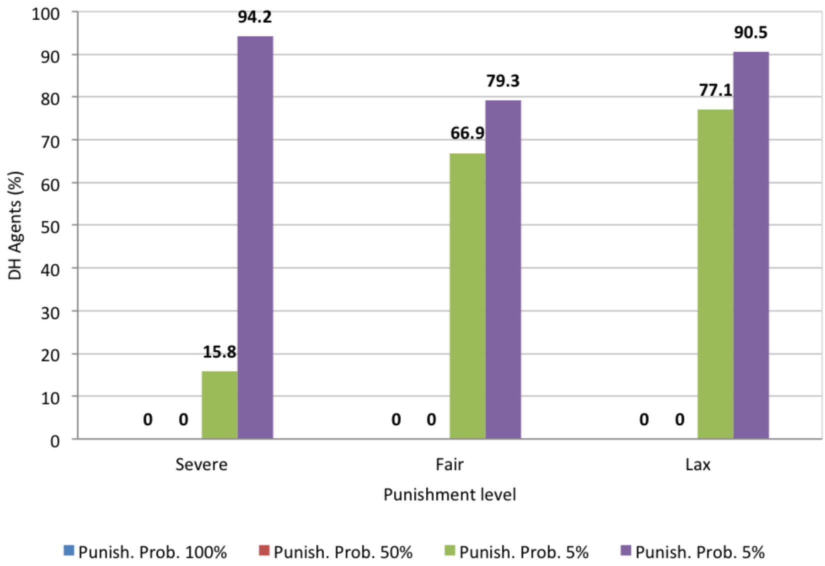

Fig. 4 – Percentage of DH agents with H payoff of 1 unit, DH payoff of 1 unit and weak social influence (average number of connections = 1.5)

5. Summary and Discussion

In this paper we have made an attempt at analyzing some social phenomena that are usually interpreted by using the concept of social norm without using the concept. The only concepts that appear to be necessary to analyze the phenomena are the concepts of other-damaging behaviours, i.e., behaviours that reduce 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 a other-damaging behaviour and therefore makes this behaviour less probable in the future. We might define a social norm as the description of a behaviour whose exhibition or nonexhibition is socially punished but, clearly, in this case the notion of social norm would be redundant and not necessary.

Furthermore, the notion of (verbal) description, at least if we interpret it literally and not metaphorically, only applies to one of the three mechanisms that societies use to reduce the incidence of other-damaging behaviours, the mechanism of written laws and regulations which is implemented by the state.

Unless societies find ways to contain other-damaging behaviours, they risk dissolution because for the members of the society the costs of participating in the society may become greater than the benefits. Although we have identified three such ways, the formal system of law at the state level, the informal system of reputation at the social level, and the system of self-punishment at the individual level, we have addressed with our simulations only the first of these three mechanisms, the formal system of laws and regulations. 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 (we are examining the role of the second and third mechanisms for containing other-damaging behaviours in some simulations currently underway).

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 nondamaging behaviours, and this conclusion is in accordance with Merton's[34] 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[35].

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

[34] R.K. MERTON, *Social Theory and Social Structure*, New York, Free Press, 1949.

[35] W. SPELMAN, *Jobs or Jails?*, in "Journal of Policy Analysis and Management", Vol. 24, 2005, n. 1, pp. 133-165.

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 very 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 exist sub-communities of interacting dishonest individuals (we define them "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[36]. Other links can be found with the idea that the attachment of an individual to the other members of his/her group will lead the individual to behave like them, and with the differential association theory[37] according to which criminal behaviour is learnable and learned in interaction with other persons. This is also linked to various theories of social control[38].

The general conclusion that can be drawn from our simulations is that if the only mechanism for containing other-damaging behaviour is the sys-

[36] E. DURKHEIM, *The Rules of Sociological Method*, New York, Free Press, 1964; D. MATZA, G.M. SYKES, *Juvenile Delinquency and Subterranean Values*, in "American Sociological Review", Vol. 26, 1961, pp. 712-719.

[37] E. SUTHERLAND, *The Professional Thief*, Chicago, University of Chicago Press, 1937; ID., *Principles of Criminology*, Philadelphia, J.B. Lippincott, 1947; T. HIRSCHI, *Causes of Delinquency*, cit.

[38] E. DURKHEIM, *The Rules of Sociological Method*, cit.; R. SAMPSON, J. LAUB, *Crime in the Making: Pathways and Turning Points through Life*, Cambridge, Harvard University Press, 1993; R. SAMPSON, *How Does Community Context Matter? Social Mechanism and the Explanation of Crime Rate*, in Sampson R., Wikstrom P.H. (eds.), "The Explanation of Crime. Context, Mechanism, and Development", Cambridge, Cambridge Univ. Press, 2006.

tem 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 only be 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[39] and as many recent studies have confirmed[40], 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 globalisation.

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 how globalisation 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. But, as we have already mentioned, our simulations should be used not only to explain existing empirical data but also to illuminate the basic mechanisms underlying other-damaging behaviours and how society can deal with them and, notwithstanding their extreme simplicity and exploratory nature, they should provide ideas for designing new policies concerning other-damaging behaviours and for examining the possible consequences of these policies.

[39] C. BECCARIA, *On Crimes and Punishments and Other Writings*, Bellamy R. (ed.), Cambridge, Cambridge University Press, 1995 (1st ed. 1764).

[40] R.L. AKERS, C.S. SELLERS, *Criminological Theories*, Los Angeles, Roxbury, 2004.