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THE IMPACT OF AGENT-BASED MODELS IN THE SOCIAL SCIENCES AFTER 15 YEARS OF INCURSIONS

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This paper provides an overview on the impact of agent-based models in the social sciences. It focuses on the reasons why agent-based models are seen as important innovations in the recent decades. It is aimed to evaluate the impact of this innovation on various disciplines, such as economics, sociology, anthropology, and behavioural sciences. It discusses the advances it contributed to achieve and illustrates some comparatively new fields to which it gave rise. Finally, it emphasizes some research issues that need to be addressed in the future.

Perhaps 15 years is a time length insufficient to provide a full retrospection of a scientific innovation, such as the incursion of agent-based models (abm) in the social sciences. Nor it is enough to evaluate its promises and failures once and for all. However, there is no doubt that today this innovation has gained momentum after the seminal contributions by Gilbert and Doran (1994), Carley and Prietula (eds 1994), Gilbert and Conte (eds 1995), Casti (1996), Epstein and Axtell (1996), Hegselmann, Mueller and Troitzsch (1996), Axelrod (1997a), Conte, Hegselmann and Terna (eds 1997), Liebrand, Nowak and Hegselmann (eds 1998), and the establishment of the *jasss-Journal of Artificial Societies and Social Simulation* in 1998.[1] 'Generative social sciences', 'social simulation', 'agent-based computational economics' and 'computational social sciences' are now a well-recognized research area around which many scientific associations and communities, conferences, and

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[1] These contributions have been the results of some foundational symposia and workshops that were held in Guilford, 1992; Siena, 1993; Boca Raton, 1995; and Cortona, 1997. These events have been crucial in the creation of a scientific community of abm scientists.

publications revolve. Furthermore, although still in its relative infancy, the recognition of this innovation by conventional science has constantly increased in recent years.[1] Therefore, time has come to discuss some first assessments.

With no pretension as a piece of history or sociology of science, this paper attempts to provide an overview on the impact of ABM in the social sciences, by i. focussing on the reasons why ABM is seen as one of the most important innovations in social science in recent decades; ii. evaluating its impact on various disciplines, *e.g.*, economics, sociology, anthropology, and behavioural sciences; iii. discussing the advances that it contributed to achieve and illustrating some relatively new fields to which it gave rise; iv. emphasizing some problems that need to be particularly addressed in the near future.

The structure of this paper is as follows. The first part succinctly introduces ABM. The second one illustrates the epistemological impact that it has exercised on social sciences so far. The third part focuses on its impact at a substantive level, by illustrating the case of economics, sociology, anthropology and behavioural sciences. Since social sciences profoundly differ in terms of approaches, methods and standards, our analysis has been conducted on each single discipline, rather than in a general view. The fourth part presents some relatively new ABM fields that blossomed in recent years in a trans-disciplinary research style. Finally, the fifth part zeroes in on some new challenges that need to be addressed in the future to strengthen this important innovation.

1. What is ABM?

There is no doubt that the last twenty years have brought a revolution in the use of computers in social sciences (Heise and Simmons 1985, Gilbert and Abbott 2005). In the past (for the most part also today), social scientists used the computer to provide analytical solutions of complicated equation systems or to estimate statistical models for data. From the 1990s onward, they have started to use computational techniques in an innovative way to simulate and analyze implications of

[1] This recognition can be seen in the increasing number of special issues devoted to ABM in well established journals, such as *American Behavioral Science*, 1999; *IEEE Transactions on Evolutionary Computation*, 2001; *Journal of Economic Dynamics and Control*, 2001 and 2004; *Computational Economics*, 2001 and 2007; *Proceedings of the National Academy of Sciences*, 2002; *Artificial Life*, 2003; *Journal of Economic Behavior and Organization*, 2004; *Journal of Public Economic Theory*, 2004; *Physica A*, 2005; *American Journal of Sociology*, 2005; *Advances in Complex Systems*, 2008; *Journal of Economics and Statistics*, 2008; *Nature*, 2009; *Synthese*, 2009; *Mind & Society*, 2009, as well as in the many reviews and/or papers published in *Science*, *Journal of Theoretical Biology*, *American Sociological Review*, *Annual Review of Sociology*, *Philosophy of the Social Sciences*, *Artificial Intelligence Review*, to name a few.

agent interaction in given social structures (Epstein and Axtell 1996, Gilbert and Abbott 2005, Epstein 2006, Miller and Page 2007).

More precisely, an 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, 2). From a technical point of view, this tool represents a turning point in the history of artificial intelligence. The rise of distributed artificial intelligence computational techniques in the 1990s and the flexible properties of the object-oriented programming paradigm on which ABM is based, allow researchers to model agents as separate or distinct parts of a computer program that may contain heterogeneous variables, parameters, and behaviour. Agents may interact by exchanging information and via communication protocols, may react to the environment, learn, adapt, and change rules of behaviour. Modellers can therefore equip computational agents with cognitive and behavioural properties typical of human agents, while the environment (*i.e.*, geographical space, institutional rules, and/or social structures) can be programmed to mimic the real social world in more or less detail.

Unlike mathematical, statistical and standard simulation models, ABM allows social scientists to: i. achieve an ontological correspondence between the model and the real-world, since individual agents can be modelled that mimic cognitive and social characteristics of real-world actors; ii. include agents' heterogeneity, *e.g.*, in terms of behavioural rules, information, resources, position in a given social structures, whereas standard mathematical models generally assume homogenous representative agents, or no agents at all, for analytic tractability; iii. study agent interaction (in various forms) and its (long-term) consequence at the macro level, so that macro outcomes can be diachronically studied as bottom-up emergent properties from local interaction (*e.g.*, Fararo and Hummon, 2005); iv. provide an explicit representation of the environment (*i.e.*, geographical space, institutional rules, and/or social structures) and the constraints it imposes on agents' behaviour and interaction (Epstein and Axtell 1996, Gilbert 2008). Social scientists can therefore study the micro mechanisms and local processes that are responsible for the macro outcome under scrutiny, as well as the diachronic impact of the latter on the former, so that the self-organized nature of social patterns can be subject to modelling, observation, replication and understanding. This relation between processes at different levels that is always difficult to capture in social science research, now may be investigated in fine detail.

ABM differs also from important computer simulation forerunners such as system dynamics, cellular automata, and microsimulation. Unlike ABM, system dynamics do not allow for modelling heterogeneous micro aspects, just interdependence and feedbacks among macro variables; cellular automata reduce the interaction of dispersed micro entities to a single homogenous parameter; while microsimulation does not include interaction (Troitzsch 1997 and 2009, Gilbert and Troitzsch 2005).

2. The Impact on Epistemology

A comprehensive history of the development and application of ABM would certainly emphasize a difference between the US and Europe (Gilbert 2000). At the risk of brutal oversimplification, in the US, ABM became popular from the 1990s onward under the influence of research on complex adaptive systems carried out under the auspices of the Santa Fe Institute. This research enterprise was ambitiously aimed to re-write the grammar of science through a trans-disciplinary focus on the general phenomenology of complex adaptive systems in biology, economy, technology, and society (Anderson, Arrow and Pines eds 1988; Waldrop 1992; Cowan 1994; Belew and Mitchell eds 1996; Arthur, Durlauf and Lane eds 1997). On the contrary, in Europe, ABM has been metabolized *prima facie* by some innovative social scientists operating within and to some extent between their own disciplines, who viewed it as 'the' social science modelling technique *par excellence* that, once applied to traditional social science issues, would strengthen the explanatory power of social sciences and improve them from within.[1]

The epistemological consequences of ABM in the social sciences can be summarized as follows: i. ABM is helping to establish 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 most social science discourse (with of course the exception of economics) (Giere 1999, Frank 2002, Buchanan 2007); ii. it has definitively contributed to promote a *generative* approach to social science research (Boudon 1979, Barth 1981, Hedström and Swedberg eds 1998, Cederman 2005, Epstein 2006), according to which modelling the structural properties of social systems and exploring their spatio-temporal development via computer simulation are crucial steps to provide generative explanations of complex social outcomes (Epstein 2006; Frank, Squazzoni and Troitzsch 2009); iii. it has helped to put the ideas

[1] Again at the risk of brutal oversimplification, this is also reflected in the difference between the interest of US computational social scientists in investigating common mechanisms of complexity by simplified models, which has tended to promote unified inter-scientific frameworks, and the interest of European social simulation researchers in focussing on agent cognition and second order emergence as peculiar features of social systems through complicated and realistic models.

of process, change and development at the core of the social science endeavour; iv. its models provide social scientists with techniques that combine deduction and induction, theory and data, speculation and observation, in domains where empirical work and theory have often been neither mutually reinforcing nor even mutually comprehensible (Axelrod 1997a); v. it has strengthened an 'issue-oriented' rather than a discipline-confined style of research that is favouring trans-disciplinary collaboration and stepping over the classic social science disciplinary boundaries, which are functional in orientation, to deal with overarching problems that affect many different aspects of social systems.

2.1. *The Primacy of Models*

The primacy of models in describing and theorizing social systems provides a way to construct theory directly on a foundation of empirical *explanandum,* via abstraction, simplification and formalism. Modelling helps social scientists to achieve precision, clarity and fine-grained distinctions that are crucial to analyse complex social phenomena, whereas these properties are difficult to derive from un-formalized narrative accounts (Hedström 2005). Consequently, it is the model itself that becomes the 'real' object of scientific investigation, since it, and only it, can be subjected to peers' scrutiny, extension, falsification, test and comparison. As testified by the difficulty of comparing and testing narrative empirical cases and abstracted un-formalized theories, it is exactly the added value of modelling that can guarantee cumulativeness of scientific results at an inter-subjective level (Giere 1999, Manicas, 2006).

The methodological debate about inter-subjective tests, model replication and alignment in the ABM social science community testify to this (*e.g.*, Axtell *et alii* 1996, Edmonds and Hales 2003). Some illustrative examples of influential models inter-subjectively replicated and extended (*e.g.*, Janssen 2007 and 2009), as well as some vivid disputes between colleagues who replicated and extended each others' models make clear the added value of modelling to guarantee inter-subjective cumulativeness of research. Examples of this are the recent debate about the Bruch and Mare's Schelling revisited model in *American Journal of Sociology* (Bruch and Mare 2006 and 2009; Van de Rijt, Siegel and Macy 2009) and the vivid dispute about Macy and Sato's trust model on *JASSS* (Macy and Sato 2002, 2008; Will and Hegselmann 2008a, 2008b; Macy 2009). At the same time, and more important, there are convincing examples that modelling guarantees the generalisation of findings, such as in the case of the large class of tipping point models that originated from Schelling (1978) and Granovetter (1978) seminal examples (see section 3.2), or the continuously growing studies on cooperation originated by Axelrod (1997a) and Novak and Sigmund (1998) (see section 3.4).

2.2. *The Generative Approach*

The idea of generative explanation has been systematised by Joshua M. Epstein in this way:

> Given some macroscopic *explanandum* – a regularity to be explained – the canonical agent-based experiment is as follows: Situate an initial population of autonomous heterogeneous agents in a relevant spatial environment; allow them to interact according to simple local rules, and thereby generate – or 'grow' – the macroscopic regularity from the bottom up [...]. In fact, this type of experiment is not new and, in principle, it does not necessarily involve computers. However, recent advances in computing, and the advent of large-scale agent-based computational modelling, permit a generative research program to be pursued with unprecedented scope and vigour.
>
> (Epstein 2006, 7).

If micro-specifications are theoretically plausible, the model based on sound empirical grounds and the simulation results stable and robust against simulation parameters, then the micro-specifications in question are said to satisfy the criterion of 'generative sufficiency' with regard to the social outcome under scrutiny. Again according to Epstein, «this demonstration [*i.e.*, *being able to generate a macro regularity of interest with an* ABM] is taken as a necessary condition for explanation itself» (*ibidem*, 8). If explaining implies generating, *i.e.*, specifying and showing the generative process through which interacting agents in a given environment combine to produce the outcome under scrutiny, then ABM can be pivotal to identify 'candidate explanations' that can further guide the empirical research. As argued in Boero and Squazzoni (2005), Squazzoni (2008) and Frank, Squazzoni and Troitzsch (2009), given the high sensitivity of social outcomes to small contextual and contingent micro details, the causal shift from discovering 'sufficient' generative explanations to identifying «necessary» ones calls for the relevance of careful empirical inspection.

2.3. *Process and Change*

One of the traditional problems of social sciences is to have methods and tools to understand the evolving nature of social structures and institutions. Every social scientist acknowledges the process nature of social phenomena, but, for sake of tractability or for lack of appropriate modelling tools, he/she uses theories and models that do not seriously reflect this belief. Computer simulation is a crucial means to put process, change and long-term dynamics at the very core of the social science research. Thanks to its capability of reproducing, synthesizing and visualizing space and time, it allows social scientists to thinking social phenomena in terms of processes that emerge from agent interaction and change over time. This is for 'rewinding the tape' and exploring different scenarios, like in many ABM applications in anthropology, historical sciences or archaeology (see section 3.2), or for capturing the mechanisms that determine the evolution of social structures or institutions in a long-term perspective (see section 3.3).

2.4. *The Un-Excluded Middle*

The modelling attitude of ABM has had innovative consequences in that it promoted a reconciliation of empirical evidence and theory in a twofold direction (Squazzoni and Boero 2005). ABM has been often viewed as a 'third way of doing science' that combines deduction and induction (*i.e.*, abduction). Like deduction, ABM starts with a rigorously specified set of assumptions regarding a system under scrutiny, but does not result in analytical proofs of theorems. Rather, it generates (artificial) data suitable for analysis by induction. At the same time, in contrast to typical induction, data comes from an artificial observed system rather than from direct measurements of the real world (Axelrod 1997b, Gilbert and Terna 2000, Axelrod and Tesfatsion 2006). Since ABM is positioned in this un-excluded middle between deduction and induction, it has impacted in different directions the social sciences, depending on the prevalence of deductive or inductive practices currently in use. In areas where mathematical formalism, abstraction and deduction were the pillars of a discipline's research style, as in economics, ABM has been a means to bring more empirically-based hypotheses into theory, helping to relax a body of highly abstracted assumptions. In particular, it has opened the possibility of introducing a complexity perspective based upon out-of-equilibrium micro-founded dynamics (see below). In disciplines where qualitative evidence, narrative descriptions and induction formed the dominant research style, as in anthropology, historical sciences and sociology, ABM has provided the possibility of increasing rigor through formalism, simplifying complex narrative constructs, and enlarging the space of application for generative explanations (see below).

2.5. *Trans-disciplinarity*

Last but not least, ABM has raised the possibility and even the promise of a trans-disciplinary reconfiguration of the disciplinary borders in social science. This process of reconfiguration has important consequences for social scientists. First, since it focuses on broad range issues, involving different entities, processes and levels, trans-disciplinarity increases the capacity of scientists to achieve theoretical generalisation and formulate taxonomies. For instance, in the trans-disciplinary field of cooperation, it is now possible to distinguish, compare and order explanatory mechanisms at the level of atoms, molecules, individuals, societies, and ecologies, so that researchers have started to thoroughly understand the general features, as well as the peculiarities that arise at any particular level. Second, trans-disciplinarity favours the spread to the social sciences of innovative modelling approaches and techniques, many of which originated in computer science or physics. Both these consequences of trans-disciplinarity will be illustrated by examples in section 3 below.

Of course, ABM is an innovation that goes beyond normal science, and is still in its infancy. We cannot today forecast all the epistemological consequences it may eventually entail. Indeed some philosophers of science even dispute our contention that computer simulation is really innovative (Frigg and Reis 2009)! In the next section, we throw caution to the winds, play the prophet and present an overview of some changes that we expect will happen in the relatively near term in the social sciences, as a result of the increasing use of ABM.

3. The Impact on Explanation

The impact of ABM at the explanatory level is, on one side, relatively easy to describe, since we have many examples of ABM that have provided convincing explanations of economic, social or historical phenomena. But, on the other side, given the heterogeneity of social sciences, in terms of approaches, challenges, methods, and scientific standards, it is difficult to systematize it into a coherent picture. This is why we have decided to distinguish the impact on single disciplines, such as economics, sociology, anthropology and the behavioural sciences.[1]

3.1. *The Impact on Economics: Lifeblood to New Foundations*

The recent financial and economic crisis has provided a dramatic example (though not the first one) of the inadequacy of conventional economics models to explain economic phenomena, as well as to provide

[1] Other areas in social science in which ABM is making an impact include: organization theory and business management (Carley and Prietula eds 1994; Prietula, Carley and Gasser eds 1998; Ilgen and Hulin eds 2000; Lomi and Larsen eds 2001; Lin and Carley 2003; North and Macal 2007; Dignum ed. 2009), political science (Cederman 1997, 2001; De Marchi and Page 2008), demography (Billari and Prskawetz eds 2003, Billari *et alii* eds 2006), geography (Gimblett 2002; Maguire, Batty and Goodchild eds 2005), criminology and conflict and war studies (Saam 1999; Tessier, Chaudron and Müller 2000; Ilachinski 2004; Liu and Eck eds 2008) and socio-cognitive sciences (Conte and Paolucci 2002, Sabater and Sierra 2005, Sun ed. 2005), to name a few.

effective policy prescriptions. Even its most advanced version, the dynamic stochastic equilibrium model, which has gained momentum also at the policy level (*e.g.*, to forecast the effect of monetary and fiscal policy or the patterns of the economic growth of a country), requires a set of unrealistic assumptions that currently are under active investigation: for instance, the perfect knowledge of economic actors, the presence of complete markets and perfect competition, and the absence of nonlinear interactions. There is increasing evidence that economic actors do not have perfect access to information, do not adapt instantly and rationally to new situations, are victims of uncertainty, are not always in position to predict and maximise their long-run profit, in particular when this possibility depends upon the decisions of other actors, and are subject to such biases as overconfidence, risk aversion, and peer pressures. Moreover, we know that the mechanisms through which markets arrive at prices are subject to multiple possible outcomes, where unpredictability seems more the rule than the exception (Farmer and Geanakoplos 2009). The adoption of familiar and highly unrealistic conventional models is a dramatic myopia particularly in case of political or financial institutions that need to «assemble the pieces and understand the behaviour of the whole economic system» (Farmer and Foley 2009, 685). This is where complexity enters the picture, with the relevance of interaction, nonlinearity, bounded rationality and incomplete knowledge. Consequently, new models and new modelling techniques are needed that look at these aspects (Durlauf 1998, Arthur 1999, Axtell 2007, Colander *et alii* 2008).

ABM in economics has been so far the principle of methodology available for a complexity-based approach to the explanation of economic phenomena, a return of economic theory to empirical evidence, and a reconciliation with social science research, in particular those areas where human cognition, social interaction and evolution matter. All the heterodox traditions in economics were traditionally stuck by the difficulty of suggesting new perspectives on economic theories and models, because of the lack of alternative formalisms and modelling techniques to show the limits of mainstream models, express new foundations and corroborate explanations. Drawing on the pioneering works on complexity by von Hayek (1967), Simon (1981), Nelson and Winter (1982), Mirowski (1989), Arthur (1991, 1994a), Lane (1993a, 1993b), and Krugman (1996), among others, in the last fifteen years a new discipline was born under the name of «agent-based computational economics» (Tesfatsion and Judd eds 2006). It is aimed to reformulate the foundations of economics starting from the following points: i. a non-standard approach to human behaviour, where economic actors are not assumed to be hyper-rational utility function maximizers and atomized entities, but rather adaptive learning agents that follow simple rules, interact and are influenced by others; ii. a realistic picture of interactions among economic actors, so that market dynamics can be investigated as emergent properties from dispersed local interactions between actors characterized by imperfect knowledge and information asymmetries; iii. the disentanglement of micro-macro correspondence functionalism typical of mainstream models, so that the invisible hand of the market does not require intelligent fingers anymore, nor any fictitious aggregation mechanism, but rather micro-macro models that look at the emergent 'intelligent' market properties from dispersed localised agent interactions.

Thanks to some pioneering examples, such as Silverberg, Dosi and Orsenigo (1988), Albin and Foley (1992) and Arthur (1994b), in recent years several important examples of ABM in economics have been published in many sub-fields, such as industrial economics (Malerba *et alii* 1999; Dosi, Fagiolo and Roventini 2006; Pyka and Hanusch 2006), labour (Pingle and Tesfatsion 2003, Richiardi 2004), innovation (Gilbert, Ahrweiler and Pyka 2007; Lane *et alii* eds 2009; Del Re *et alii* 2009), macroeconomics (Kirman and Vriend 2001, Cantner *et alii* 2001, Lim and McNelis 2008), and financial markets, to name a few (Brock and Hommes 1998, Lux and Marchesi 1999, Hommes 2002, Chiarella and He 2003, Axtell 2007).

Given the pressurizing urgency of the present crisis, the best example to quote in this paper is the Santa Fe Institute Stock Market model, which was created in the early 1990s by W. Brian Arthur and colleagues (Palmer *et alii* 1994 and 1997; LeBaron 2000; LeBaron, Arthur and Palmer 2003, Ehrentreich 2008). This is a well-known contribution that has shown the potentials of ABM to remove some restrictive assumptions required by standard models for tractability and to explain particular features of the stock market, such as bubbles and crashes, which are unexplained by conventional models. It dispenses with the notion of a representative agent, the assumption of perfect knowledge behind rational expectations, and the efficient market hypothesis, in favour of agent heterogeneity, inductive learning and minimal rationality. The aim is to explain some puzzling stylized facts on stock markets, such as non-normal return distributions, volatility clustering of returns, and other far from equilibrium outcomes. The model casts light on emergent market patterns (the *explanandum*) starting from endogenous interactions between heterogeneous agents who continually adapt their expectations to the market, which aggregates their time-varying expectations and the behaviours to which they give rise. The idea of the predictive power of minimally rational agents with respect to the emergent patterns of stock market prices in reality has been also confirmed by subsequent ABM studies (Farmer, Patelli and Aovko 2005; Farmer and Foley 2009; Buchanan 2009).

Following this inspiration, but departing even further from the neoclassical model, Hoffmann, Jager and Von Eije (2007) have worked on an empirically calibrated stock market model that incorporates empirical data from a survey of individual investors' decision-making styles and their social interactions. This model emphasizes the relevance of simple behavioural heuristics and imitation within social networks to explain market dynamics like price and return time series. The simulations produce time series very similar to real data of the Dutch stock market (like the asset returns distributions). Another example is the Thurner, Farmer, and Geanakoplos' stock market model (2009), which aims to understand how leverage affects fluctuations in stock prices. This model represents the interaction between heterogeneous agents like noise traders, hedge funds, investors and a bank. The simulations generate price patterns very similar to empirical data and suggest that the immediate cause of crashes is the risk control policy of the banks. Banks protect themselves by putting a limit to leverage, so when a fund exceeds its leverage limit, it must partially repay its loan by selling the asset. Unfortunately this sometimes happens to all the funds simultaneously, when the price of the asset has already begun to fall. The resulting positive feedback amplifies downward price movements. In extreme cases, this causes crashes, but the effect can be seen at every time scale, producing a power law of price disturbances. It is therefore the very effort to control risk at the local level that creates excessive risk at the aggregate level, which shows up as fat tails and clustered volatility (Farmer and Foley 2009).

In sum, these examples indicate that ABM may be better equipped than conventional models to capture the essential structural patterns of complex economic systems, since patterns, rather than being analytically deduced, are modelled and understood as resultant outcomes of empirically grounded and theoretically plausible agent interactions (Terna 2000, Farmer and Foley 2009, Buchanan 2009). Last but not least, by focusing on agent interaction and emergent patterns, ABM provide a way to reconcile economics with other related disciplines, including behavioural science, economic history, psychology and sociology, not to mention the collaboration with computer scientists and physicists who have experience in modelling large scale complex systems. These reconciliations and collaborations open up the possibility of attaining a deeper understanding of economic phenomena that current standard methodologies permit.

3.2. *The Impact on Sociology: From Factors to Actors*

In a recent survey, Macy and Willer (2002) have synthesized the impact of ABM on sociology as a shift of the sociologists' attention «from factors to actors». Largely inspired since the 1960s by structural-functionalism, cybernetics and the first wave of complex systems theory (Sawyer 2005), before ABM the standard way to approach social outcomes through computer simulation was to model systems' properties as a set of differential equations that related interdependent aggregate factors, at a local level. With such an approach, researchers were necessarily more directed towards prediction and forecasting than towards understanding and explanation.

The advent of ABM has marked a new era in sociology, where computation is not used to solve systems of differential equations, nor to estimate statistical models for data, but to formalize models of agent interaction and micro aspects to understand such social outcomes as the emergence of norms or the diffusion of innovations. Largely inspired by Schelling's (1978), Granovetter's (1978), Boudon's (1984) and Coleman's lessons (1990), the ABM perspective emphasizes the idea that, by relating macro-level social outcomes to the motivations and interactions of micro-level agents, sociology can provide more informative explanations than by purely aggregated analyses (Hedström and Swedberg eds 1998, Hedström 2005, Bruch and Mare 2006).

In doing so, ABM favours a methodologically individualistic approach in sociology, while at the same time allowing for the role of social structures and institutions in constraining and providing opportunities for individual action (Udehn 2001). As I have suggested in Squazzoni (2008), this helps sociologists to 'secularize' the longstanding debate on the micro-macro link. Since this link is a hard nut to crack, the use of modelling and simulations capable of paying attention both to agency and social structures and institutions and capturing their mutual influence, is a good research strategy to skirt the marshes of any 'egg or chicken' ontological dispute and to translate the debate from a foundational and philosophical level to a more pragmatic one (Saam 1999, Squazzoni 2008). As shown by Granovetter (1978) and Granovetter and Soong (1986, 1988), formalisation and modelling prepare sociologists to understand the many puzzling, sometimes bizarre and surprising social outcomes that social life has in store better than the traditional quantitative or qualitative approaches, too much focused on a single level of analysis.

In general, ABM in sociology has been so far addressed to two explanatory challenges: i. understanding the self-organized nature of social structures and collective dynamics from the bottom-up, and ii. understanding the aspects of social structure that give rise to social order, cooperation and collective outcomes (Macy 2002, Macy and Willer 2002). Most of the current sociological ABM can be clustered around these two research streams. While the former examples emphasize the relevance of iterative local interaction to explain the emergence of collective dynamics and structures, following a bottom-up inspiration, the latter are more focused on the relevance of social embeddedness to explain social outcomes.

The roots of the first type of models trace back to the famous Schelling segregation model (1978). Schelling's purpose was to illustrate the dynamics of residential mobility and segregation by race and ethnics, *i.e.*, a long standing pattern of many large cities in the US. In his simple and abstracted model, first elaborated by placing back and white pieces on a chessboard, he showed that individual preferences about where to live can combine in aggregate spatial patterns under the influence of the spatiotemporal interdependence of individual choices.

The first version of the model is based on a rectangular grid of cells, which represents an idealised urban space. In this space, cells represent a home-site that can be occupied by a household, black or white, with about a quarter of the cells that are empty. The assumptions are that agents (households) are of two groups (black or white), prefer to have a certain percentage of their neighbour of the same group (50% or more), have a local vision (a Moore neighbour composed of eight agents), can detect the composition of their neighbours and are motivated to move to the nearest available location where the percentage of like neighbours is acceptable. Allowing households to interact in space, results in households reaching their tipping points with a spiral effect, because of the interdependence of move/stay choices of households across time and space. Anyone who reaches his/her tipping point and moves out of the neighbourhood reduces the number of households of the group he/she belongs to in the neighbourhood leaving whoever is a little closer to his/her tipping point. Moreover, this implies that subsequent entrants who take the place of those who leave are predominantly of the minority, and that the process ultimately and irreversibly changes the composition of neighbourhoods. The evidence is that segregation does not require racist agents to occur. It is an emergent property that is strongly dependent on interaction mechanisms where agents influence each other locally according to a temporal sequence. Vice-versa, by looking residential patterns in many large cities just at the aggregate outcome, one would expect that segregation would have been caused by explicitly 'segregative' agents!

The Schelling segregation model has inspired a robust research stream where segregation mechanisms have been thoroughly explored, corroborating the evidence that formalized models encourage the cumulativeness of scientific progress. Epstein and Axtell (1996) extended the tolerant thresholds in individual preferences to show that even a little racism is enough to tip a society into a segregated pattern. While Gilbert (2002) extended the original model to take into account macro variables such as crime and neighbourhood history, Zhang (2004) investigated the impact of relevant economic variables. Laurie and Jaggi (2003) and Pancs and Vriend (2007) investigated the effect of the enlargement of the mobility of households and preferences toward integration. Bruch and Mare (2006) investigated through an empirically calibrated ABM the dependence of Schelling's findings from the type of threshold behaviour and showed that continuous function preferences, allowing households to adapt to neighbourhood composition and change continuously, can reduce residential tipping.

Thanks also to the classic contribution by Granovetter (1978) on the emergence of collective behaviour, these examples now are part of an entire class of models known under the label of 'tipping point' models that explain very different kinds of social outcomes with the same type of mechanism, such as the rise of social movements (Hedström 1994), the diffusion of crime (Picker 1997), opinion dynamics (Weisbuch *et alii* 2002, 2005; Deffaunt *et alii* 2002), the emergence of civil wars (Cederman 2003), or the persistence of minority cultures (Axelrod 1997a). The explanatory power of these models has also been the subject of some popular books, such as Gladwell's *Tipping Points* (2001) and Ball's *Critical Mass* (2004). Granovetter (1978, 1442) summarized in the following way their added value:

> By explaining paradoxical outcomes as the result of aggregation processes, threshold models take the 'strangeness' often associated with collective behaviour out of the heads of actors and put it into the dynamics of situations. Such models may be useful in small-group settings as well as those with large numbers of actors. Their greatest promise lies in analysis of situations where many actors behave in ways contingent on one another, where there are few institutionalized precedents and little pre-existing structure [...]. Providing tools for analyzing them [*these situations*] is part of the important task of linking micro to macro levels of sociological theory.

The roots of the second type of models trace back first to Axelrod's works (1984, 1997a), Macy's works (1991, 1995), and to some foundational contributions by Nowak and Sigmund (1992, 1993 and 1998), which largely overlap with the themes of behavioural sciences (see below for an overview that covers also sociology issues). Fehr and Gintis (2007) have provided a comprehensive survey on the relevance of these studies for the advancement of sociology. There is evidence that in this way sociologists and behavioural scientists can overcome the ongoing foundational dichotomy between the *homo oeconomicus* and the *homo sociologicus*, since these models provide: i. new behavioural foundations for sociology models; ii. concrete and empirically verified explanations of the social structure effects that make self-regarding or norm-regarding behaviours (in all their variants) predominate at a population and evolutionary level.

Thanks to ABM, many interesting properties of interaction networks have been discovered that might influence the emergence of robust patterns of systemic cooperation among rational agents that face a social dilemma. For example: interaction stability (Cohen, Riolo and Axelrod 2001); trust-based network density (Macy and Skvoretz 1998); tag mechanisms, which guarantee the evolutionary sustainability of cooperation even in absence of reciprocity motivations (Hales 2000; Riolo, Cohen and Axelrod 2001; Axelrod, Riolo and Cohen 2002; Axelrod, Hammond and Grafen 2004); and the circulation of reputational information across and within social groups (Hales 2002, Conte and Paolucci 2002, Janssen 2006). As shown in Bowles and Gintis (2004), one of the best example of the potential of ABM to combine experimental evidence and sociological aspects in a sound evolutionary framework (which is presented below), these studies make a closer collaboration between sociologists and experimental behavioural scientists crucial more than ever to move towards a unified framework to understand the effect of social structures on the evolution of social behaviour. This is an area where dramatic progress can reasonably be expected in the next future.

Finally, examples more embedded in the traditional sociological literature exist that focus on generative explanations of social structure effects on social outcomes, largely inspired by a 'Coleman boat' style of explanation (Coleman 1990), according to which a given social outcome is understood as a change at the macro level that results from agent interaction within given macro-situational constraints. One of the most influential has been Mark's model on social differentiation (Mark 1988), where social differentiation, rather than being explained in functionalistic terms, is explained as a self-organized agent interaction outcome. This model helps to understand how aspects of the social structure (*e.g.*, size of the social groups or homophily) influence agents' behaviour, which in turn generate a change in the social structure and so on, until the system stabilizes in robust and clear differentiation patterns. Another example is Manzo's empirically grounded ABM of education stratification and social inequality, where the unequal empirical distribution of high level diplomas in French and Italy over time is explained as the result of the social origin of groups and the interdependence of students' choices (Manzo 2007a). These examples provide strong arguments for the advantage of models that combine attention to structural factors and agent interaction for the explanation of complex social outcomes.

In conclusion, the impact of ABM in sociology seems to encourage an effective convergence between action and structure paradigms on a pragmatic modelling plane (Squazzoni 2008). While the former find in ABM a means to understand the relevance of institutions and social structures in explaining the aggregative outcomes of agent interactions, the latter find a means to combine macro data analysis and generative explanations (Hedström 2005, Manzo 2007b).

3.3. *The Impact on Anthropology: A Model-Based View of Science*

The impact of ABM on anthropology has been more marginal that in economics or sociology but not less important, in particular since it provided some first interesting examples of representations of social systems that include space, time, ecology and evolution. In this case, ABM has provided room for a formal model-based view of science in areas where qualitative accounts and empirical details have in the past dominated the scene, and subjectivism and narrativism are the most influential paradigm.

In anthropology, ABM has been so far the means to: i. combine intensive field observation and formal modelling to the benefit of both; ii. bring the anthropologists' attention back to the analysis of the macro properties of social systems, by purging any functionalistic drift and putting agency at the core of any explanation; iii. embed anthropology into a socio-natural long-time evolutionary perspective, so that cases of particular human groups have begun to be generalized through comparison along a scale of increasing social and political complexity (Kohler 2000, Wright 2000, Kohler and van der Leeuw 2007).

In general, ABM has allowed anthropologists to come back to system-level analyses without the typical naïve functionalistic flavour of the systems ecology models suggested in the past. This functionalism touched off the irate reaction of many qualitative anthropologists against formal modelling and computer simulation *tout court*. On the contrary, by using simulation models to 'rewind the tapes' and investigate the long-term consequences of relevant social and ecological parameters on social evolution, anthropologists can demonstrate that material constraints do not mandate a specific set of cultural or social responses, nor any teleological or functionalistic explanation (Lansing and Kremer 1993).

A first example in this direction was the Lansing and Kremer (1993) model of a Bali farmers' community. This community was subject to a crisis from the 1960s onwards caused by the Green Revolution. Top-down planners inveighed against the old social structures used by farmers to manage irrigation and agriculture, in favour of mass agriculture technology progress. Using an empirically grounded ABM, Lansing and Kremer showed how socio-cultural Bali structures were co-evolving with their environmental constraints into a self-organised sustainable path. The simulation results helped to show how past social structures were more adaptive than Green Revolution-inspired mass agriculture technologies, so that the resistance of farmers against the mantra of technology progress was not driven just by religious conservatism as the planners had claimed. The persuasiveness of this model and its results also helped policy makers change their approach.

This seminal contribution has been really influential in giving rise to a large research stream in last ten years, directed towards understanding the mechanisms of the self-organised governance of the commons and the problem of collective action at the local level, by combining social, institutional and ecological aspects (Becu *et alii* 2003, Barretau *et alii* 2004). Recently, Janssen (2007) has come back exactly to Lansing and Kremer's model to test a generalization of their findings for the analysis of self-organized common governance. This research is very important to investigate the relevance of decentralised social institutions to guarantee sustainable development paths in complex social systems, where agents are heterogeneous, self- or other-regarding, pursue conflicting goals and interact in complex ways (Lansing and Miller 2005, Janssen and Ostrom 2006).

Another example of a retrospective ABM is the Anasazi model developed by a large multi-disciplinary research team at Santa Fe Institute. This example allows us to appreciate the pivotal function of ABM in allowing researchers to rerun history to explain complex patterns of long-term social evolution. This model was aimed to explain the history of an ancient community that inhabited the Four Corners area in the American Southwest between the last century BC and 1300 AD and disappeared from the region in a few years without evidence for enemy invasions or dramatic environmental catastrophes (Ware 1995, Dean *et alii* 2000). The rationale for using ABM was the attempt to overcome some traditional problems in the field of evolutionary studies of prehistoric societies. These were as follows: i. the tendency to adopt a 'social systems' theoretical perspective, which implied an overemphasizing and a reification of the systemic properties of these societies, ii. the exclusion of the role of space-time as an evolutionary explanatory factor, and iii. the tendency to conceive culture as a homogenous variable, without paying the due attention to evolutionary and institutional mechanisms of transmission and inheritance of cultural traits.

The Anasazi model was based on an impressive use of great quantities of empirical environmental and social data to build realistic retrospective simulations. For instance, a land fertility index to simulate a realistic production landscape was calibrated on different geographical areas within the valley where the Anasazi lived. This calibration required a huge amount of data from many sources, including dendroclimatic, soil, dendroagricultural and geomorphologic surveys. These data were used to calculate climate and hydrological changes, soil composition, and the productivity of the species of maize available in the valley at that time – all disaggregated for each hectare and each year! Social data incorporated information relevant to household settlements with heterogeneous features, such as age, location, and grain stocks, and common features, such as the organization of houses age of death, nutritional needs and information processing and decision capabilities.

The simulation results were capable of reproducing empirical evidence on the Anasazi evolutionary trajectory, such as their dynamic distribution in space and their resistance against environmental changes. They also led the team to reject the hypothesis that the pressures of environmental change were responsible for the Anasazi exodus from the region and to promote instead the explanatory power of more socio-political 'pull' factors, such as the influence of leaders.

Similar types of studies have been carried out by Berger, Nuninger and van der Leeuw (2007), who developed an empirically calibrated ABM of the Middle Rhône Valley between 1000 BC and AD 1000 to study how particular socio-cultural structures can explain the evolutionary resilience of ancient social systems against environmental perturbations; and by Varien *et alii* (2007) and Kohler *et alii* (2007), who used an ABM to understand the long-time co-evolution of households' settlement patterns and environmental constraints in the Prehispanic Central Mesa Verde Region between AD 6000 and 1300; and by Wilkinson *et alii* (2007), whose ABM explains the emergence pattern of cities in southern Mesopotamia during the Bronze Age.

Although the cause of computer models in anthropology and archaeology have been advocated since the 1960s (Fisher 1994) and 1970s (Doran 1970, Thomas 1972, Doran and Hodgson 1975), these recent examples provide a new and important direction for at least four reasons. First, each of them casts light on mechanisms and suggested explanations that could not have been invoked without the help of modelling and simulation. As remarked by Small, Blankenship, Whale (1997), 'computer modelling allows the kind of analysis ethnographers say they want to do but rarely accomplish with linguistic description', that is, the possibility to understand human behaviour in a larger cultural and historical context. Second, behind each model mentioned above, there is an impressive empirical/field work on archaeological records, environmental and demographic databases, textual evidence and historical documents on socioeconomic structures and human behaviour. In this respect, these examples show how flexibly and powerfully ABM can be in incorporating quantitative and qualitative empirical precision in formalized models. Third, by building empirically realistic simulation models, the cited researchers have combined environmental, demographic, social, and cultural aspects that are usually partitioned among different disciplinary fields, and they have synthesized these aspects into convincing accounts of episodes of social evolution. Finally, these models have allowed researchers to verify and test explorative theoretical hypotheses in a serious and robust way, so that cumulativeness of evidence has been achieved, whereas traditional anthropological studies get stuck in suggestive qualitative case-studies and narrative descriptions that only with extreme difficulty, if at all, result in a cumulative and coherent story.

3.4. *The Impact on Behavioural Sciences: Taking on Social Evolution*

Since the seminal contributions by Axelrod (1997a) and Novak and Sigmund (1998), one of the strongest impacts of ABM has been on evolutionary game theory and experimental behavioural sciences, particularly in the study of human cooperation and social dilemmas. In this field, ABM has been ancillary to the laboratory, in that it extended experimental evidence (usually based on some game-theory driven stylized interaction) in a social science direction, by analyzing consequences of subjects' behaviour at the macro social level and in a long-time evolutionary perspective. At the same time, ABM has provided a guide for further experimental research, by revealing new potential behavioural mechanisms or by emphasizing the impact of some structural aspects in the experimental games (Duffy 2006).

One of the best example is the Bowles and Gintis' model of the evolutionary and social foundations of strong reciprocity, empirically grounded in the case of mobile hunter-gatherer bands in the late Pleistocene (Bowles and Gintis 2004). Experimental evidence indicates that cooperation in human groups is undermined by low genetic relatedness among group members. The authors explain that humans have a social predisposition to punish those who violate group-beneficial norms, even when this imposes a fitness cost on the punisher (*e.g.*, Fehr and Gätcher 2000 and 2002). Where members of a group benefit from mutual adherence to a social norm, strong reciprocators obey the norm and punish its violators, even though as a result they receive lower payoffs than other group members, such as selfish agents who violate the norm and do not punish, and pure cooperators who adhere to the norm but free-ride by never punishing. Their ABM shows that, under assumptions approximating likely human environments over the 100,000 years prior to the domestication of animals and plants, the proliferation of strong reciprocators when initially rare is highly likely, and that substantial frequencies of all three behavioral types are sustained in a population. In fact, the simulations allow the researchers to identify a population level selective mechanism among and within groups (*e.g.*, Bowles, Choi and Hopfensitz 2003) that explains the reason why reciprocators achieve fitness advantages on cooperators over time when social groups are porous, since the latter are easily exploitable by selfish agents and decrease the fitness of their respective group. In sum, these results show that these three types of behaviour and their particular mix are evolutionarily functional to the social order and the social life in human groups.

Duffy (2006) has provided an extensive survey on examples of ABM and lab experiment combinations, with overlapping issues with experimental economics and behavioural finance. This survey testifies to the importance of this innovative research area. Examples range from: i. the 'zero intelligence' agent trading models, where ABM has been used to simulate rationally minimal agents that produce higher performance than real human agents in structured market institutions (*e.g.*, Gode and Sunder 1997); ii. inductive learning trading models, where experimentally calibrated ABM, similar to those on financial markets mentioned above, have been used to identify learning mechanisms undertaken by human agents in complex market situations (*e.g.*, Arthur 1991); iii. evolutionary trading models, where genetic algorithms and other computational techniques have been used to model subjects' behaviour so as to understand, for instance, under which conditions an experimental population of adaptive agents learn optimal bid functions in a variety of auction formats (*e.g.*, Andreoni and Miller 1995).

More recently, Rauhut and Junker (2009) have developed an experimental data-driven ABM that investigates the link between bounded rationality of human agents and punishment in crime situations. Janssen, Radtke and Lee (2009) have developed an experimental data-driven ABM that helps authors to map the behavioural patterns in a dynamic common dilemma better than traditional statistical analyses. Together with some colleagues, I have created an ABM based on experimental data on behaviour of a population of human subjects who played an iterative investment game in the lab, which helps us to understand the positive effect of partner's selection on cooperation (Boero, Bravo and Squazzoni 2009). In another experimental-data driven ABM on investment decisions undertaken by subjects in the lab, we have found evidence on the relevance of reputation for the exploration capabilities of agents in uncertain environments and the robust resilience of the reputation system against cheating (Boero *et alii* 2009). These examples show that, without the help of ABM, it would have been impossible to generalize the experimental findings and investigate related aspects of social structure and evolution.

At the present, there is no doubt that the integration of game theory, lab experiments and computer simulation is one of the most solid research streams that connects behavioural and social science to explain social outcomes and evolution (Duffy 2006, Gotts *et alii* 2006, Fehr and Gintis 2007, Gintis 2009). This integration can be positive for social scientists for two reasons. First, it can help to test whether the experimental evidence about human behaviour (rigorously collected in the lab or, in some cases, also in the field) can be generalized to explain the evolution of social groups and structures. Secondly, simulation results can be used in turn to inform the experimental design towards new lines of research (Macy and Flache 2002, Duffy 2006).

Of course, it must be noted that all the disciplines that now revolve around the study of social behaviour, such as economics, sociology, psychology, anthropology and biology, have their own research foci and their own models of individual behaviour and interaction, which at the present are still largely incompatible (Gintis 2009). Notwithstanding, these first examples can help to perceive the potential added value of a theoretically and methodologically unified perspective in the study of social behaviour that steps over the feudal structure of the disciplines. As suggested by Bowles (2009), these potentials are not only confined to analytical purposes, but can be of paramount importance to provide a more realistic picture of social behaviour that should inform mechanism design options and policy solutions.

4. New Fields

Besides the impact on well established disciplines, ABM has also encouraged new fields to blossom over in recent years around some crucial issues that have required multi-disciplinary collaboration and impacted different disciplines, such as social norms, networks, multi-agent systems and socially-inspired computing, socio-natural evolution, and policy modelling (this is not an exhaustive list). Some examples of this have been already mentioned before.

The study of social norms through ABM has combined and synthesized contributions from cognitive sciences, experimental behavioural sciences, evolutionary game theory, and cultural evolution studies (*e.g.*, Conte and Dellarocas eds 2001, Bowles 2004, Sun ed. 2005, Boissier *et alii* 2006). Two aspects have been particularly explored, which are mutually complementary: i. how social norms emerge in spontaneous self-organized ways from localized agent interaction (Young 1998, Epstein 2001, Hodgson and Knudsen 2004) and ii. how they impact on agent cognition by amplifying or deviating the normative social pattern (Conte and Castelfranchi 1996, Conte *et alii* 2001, Conte *et alii* 2007). On these aspects, these works have started to accumulate strong evidence that is expected to cast light on some recent puzzles on the long-time co-evolution of institutions, norms and human cognition that is also on the radar screen of many influential historians and economists (Bowles 2004, North 2005). For the advancement of these studies, the combination of laboratory experiments and ABM is of paramount importance.

The study of networks is a trans-disciplinary field spanning physics, biology, computer sciences, mathematics, evolutionary game theory and social sciences, especially sociology. It is aimed to define the common structural properties and the macro consequences at system dynamics level of diverse network forms to explain the spread of disease, the diffusion of innovation on markets, the emergence of terrorism, the robustness of Internet and other important empirical issues (Newman, Barabási and Watts 2006; Barrat, Barthélemy and Vespignani 2008; Jackson 2008; Naimzada, Stefani and Torriero 2008). Largely inspired by pioneering works and best-sellers like Watts (1999), Buchanan (2002) and Barabási (2002), it is now a huge trans-disciplinary field that pursues the building of a 'science of networks', with overlapping and promising cross-fertilization with ABM (*e.g.*, Monge and Contractor 2003). In particular, ABM and network modelling (*e.g.*, random graphs, small worlds, scale-free networks) can combine attention to action and structure, so as to understand the systemic consequence of agent interaction that is embedded into structural patterns of social systems. Interesting examples in sociology are abundant in many fields, such as the study on the growth of inter-organizational collaboration in the life science by Powell *et alii* (2005), the empirical study of the Afghan power structures by Geller and Moss (2008), the empirical study on the emergence of binge drinking in the UK teenagers by Ormerod and Wiltshire (2009), as well as the studies on the evolution of altruism by Németh and Takács (2007), the emergence of consensus or conflict by Buskens, Corten and Weesie (2008), and the reputation-based cooperation in dynamic networks by Corten and Cook (2009), that have paid close attention to lab experimental foundations as well. These examples are of paramount importance to untie crucial empirical social puzzles by combining attention to empirical/experimental evidence on agent behaviour and structural properties of social systems.

As mentioned above, another solid and growing field is the study of socio-ecological systems, where attention to environmental, social and institutional aspects is combined, and ecology and social sciences are synthesized in empirically grounded models. The aim is to analyze the self-organized governance of commons and socio-ecological resources (Janssen ed. 2002, Grimm and Railsback 2005, Matthews *et alii* 2007). In the light of the famous Lansing and Kremer's model presented above (1993), this field has unequivocally demonstrated the potentials of ABM not only as strong analytical tools, but also as a research-action method to supporting decision at a local community / region level (Costanza and Ruth 1998; Becu *et alii* 2003; Etienne, Page and Cohen 2003). This field is cross-fertilizing another important area called 'policy modelling', where ABM is used as a means to overcome the traditional policy approach based on predictions and external prescriptions towards participatory models where stakeholders are involved in the modelling and the management of the problem (Moss 2002, Barreteau *et alii* 2004, Moss and Edmonds 2005, Pyka and Werker 2009, Squazzoni and Boero 2010).

'Multi-agent systems and simulation' and 'socially-inspired computing' are lively overlapping fields that criss-cross computer sciences, distributed artificial intelligence, engineering, cognitive and social sciences (Ferber 1999; Edmonds *et alii* 2005; Brueckner *et alii* eds 2006; Clymer 2009; Fabien, Ferber and Drogoul 2009). They are aimed to provide the foundations for the understanding of the common properties of distributed intelligent system processes across different fields, so that operational technology systems' applications are designed, devised and developed that imbibe evidence from cognitive and social sciences. This is an example of how cognitive and social sciences can contribute to provide solutions and to design intelligent artificial systems, with relevant implications also in the field of robotics and the design of artificial/human agent collaborative technologies (see the Swarm intelligence field in Bonabeau, Dorigo and Theraulaz 1999; Kennedy, Eberhart and Shi 2001; Dautenhahn and Nehaniv eds 2002; Dorigo and Stützle 2004), and overlapping evidence that span from the study of artificial markets to online communities and p2p systems (Marcozzi and Hales 2008, Paolucci 2009). These supposed-far-away research areas suggest solid findings that pressurize cognitive and social sciences to dialogue towards a trans-disciplinary grammar (Hales and Patarin 2005).

5. Concluding Remarks

After 15 years of active exploration, even the most enthusiastic supporter could not argue that ABM has yet dramatically changed the current landscape of social sciences. Nevertheless, as this paper has reported, there is enough evidence that ABM is poised to change it, perhaps significantly, in the relatively near future (Lazer *et alii* 2009). We believe that this process will have positive consequences for the explanatory power of social science. Of course, it could be improved and actually sped up if some critical difficulties in the current situation would be taken seriously into account by ABM modellers (Rosser 1999).

A first critical point is the lack of a common methodological standard on how to build, describe, analyze, evaluate and replicate ABM (Richiardi *et alii* 2006, Galán *et alii* 2009). This lack has seriously penalized a wider recognition of ABM in standard science (Gintis 2007).[1] Although variety, heterogeneity and exploration are the expected rules in phases of infancy of a new 'a-normal' scientific approach, it is to be hoped that the ABM community gets out of the current 'hand-crafted' phase to enter in a new phase, were standard practices, methods and scientific communication can get stronger and cumulate step-by-step (Frank, Squazzoni and Troitzsch 2009, 8). In this sense, a crucial advancement will be achieved when the community will be capable of converging towards a 'computational *lingua franca*' through which it will be possible to establish common modelling methods that will promote comparison between models, improve replicability of results and facilitate evidence cumulativeness (Goldstone and Janssen 2005, 428). Some methodological important steps-forward have been already done in this direction, particularly on empirical validation (*e.g.*, Boero and Squazzoni 2005; Windrum, Fagiolo and Moneta 2007; Marks 2007; Moss 2008) and replication (*e.g.*, Axtell *et alii* 1996, Edmonds and Hales 2003, Rouchier *et alii* 2008, Janssen 2009). But, this ought to be generalized to all the other important aspects mentioned above, such as how to build, describe and evaluate ABM.

Another critical point is the capacity to impact the policy process by developing innovative and 'user-friendly' policy instruments with ABM. Traditional forecast-oriented policy models often fail their purpose by prescribing *ex-ante* solutions and *prêt-à-porter* recipes that dramatically underestimate the entire policy process, including the reaction of agents to policy decisions, the aggregate effect of their interactions and their systemic consequences on large spatial-temporal scales (Moss 2002, Squazzoni and Boero 2010). Apart from the interesting examples

[1] On one hand, it might be noted that reviewers and colleagues rarely are in position to gain access to the dataset of an empirical or an experimental study, so that this same problem of opacity of ABM would eventually characterize the entire scientific endeavor. On the other, it must be noted that this problem is crucial when an ABM is aimed to achieve theoretical findings and generalization by deductive proofs. This is where the practices and the methods of analytic conventional science have set a robust longstanding argumentation standard still hard to achieve with ABM.

of policy applications in the economy reported by Buchanan (2009) and the many examples of ABM applications to manage socio-ecological systems at a community level mentioned above (Costanza and Ruth 1998; Janssen ed. 2002; Etienne, Page and Cohen 2003; Bousquet *et alii* 2005), a good example of an ABM approach to policy issues is the empirically calibrated model of the Manchester City Region in Rosewell *et alii* (2008). This model has been used to support policy makers in finding strategies to improve innovation in this regional economic system. The authors studied the relevance of links between firms for innovation in certain strategic sectors that are affected by a period of deep crisis and restructuring. The purpose of the analysis has been to make the system understandable for policy makers, draw informative implications and provide clear solutions for appropriate policy support for the regional growth. The analysis has been based on a model that combined quantitative data from a large surveys on 1,500 firms, qualitative evidence drawn from interviews conducted on businesses, trade associations and agencies, and an on-line panel survey on business networks.

The recent global crisis and the evidence of the umpteenth failure of traditional policy models can now open new possibilities for unconventional approaches (Buchanan 2009). Our opinion is that the future success of ABM, especially their rivalry with conventional models, will be determined also at the policy level. What is needed is to improve the capacity of computational modellers to provide better models for policy purposes and innovate the way policy is currently formulated, managed and evaluated (Finch and Orillard 2004, Rossi and Russo 2009, Squazzoni and Boero 2010).

Finally, and most important, one of the crucial point for any future progress is to reduce the ABM divide of social scientists. The prevailing humanistic background of most social scientists, as it has been institutionalised so far, poorly equips them to appreciate the added value of formalisation and modelling. Economists and sociologists are trained at best in mathematical and quantitative methods, both during under- and post-graduate years, whereas computational methods and programming languages are largely absent from their curricula. While this deficiency undermines the potential benefits of the trans-disciplinary collaboration with other scientists, it also guarantees relevant competitive advantages to physicists and computer scientists in setting the pace of this innovation also within the social sciences.

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