Flaminio Squazzoni

The Micro-Macro Link in Social Simulation

Ente di afferenza:
_()_

Focus

The Micro-Macro Link
in Social Simulation

by Flaminio Squazzoni

1.   Introduction: the Micro-Macro Link in Sociology

The debate on micro foundations versus macro properties of societal systems lies at the very base of our discipline [e.g. Alexander *et al*. 1987; Huber 1991; Ritzer 1990; Sawyer 2005]. On the one hand, many supporters of rational choice and of sociological *subjectivism* argue that explanations of social outcomes should be reduced to individual reason and meaningful action. On the other hand, structural sociologists and the advocates of social system theories argue that sociology should dissociate itself from behavioural sciences to understand the concrete ontologies of social reality (such as "norms," "cultures," and "roles"), in terms of structures and their forms and functions. According to this view, macro social properties, as well as individual actions, are understood as produced by other macro social properties.

In the first approach, the role of social structures and constraints upon individual action is taken for granted. At the opposite extreme, supporters of the sociological ontologism over-emphasise the importance of social structures, while under-representing the relevance of individual heterogeneity and action [Granovetter 1985]. The few sociologists who have tried to venture into the realm of the "excluded middle" between these two extreme positions, such as Elias [1969; 1970] or Giddens [1986], have come under close criticism from both sides.

The strength of these dichotomies can also explain the twofold and contradictory meaning that sociologists attach to the term "emergence." On one side, there are authors like Coleman who stress the relevance of understanding how individual actions combine to generate emergent properties at a macro social system level. In-

troducing the concept of "emergence," Coleman firmly states that "the only *action* takes place at the level of individual actors, and the 'system level' exists solely as emergent properties characterizing the system of action as a whole" [Coleman 1990, 28]. On the other side, authors like Archer [1995] and, more recently, Sawyer [2005], stress that emergent social structures at a macro level can exercise causal power (and consequently can *act*) on individuals at a micro level. The macro social level is viewed as a "social stratum" populated by ontological entities that are distinct from lower entities, i.e. individuals.

The concept of "emergence" has therefore been involved in corroborating contradictory arguments. Even the vast philosophical and epistemological literature on the epistemological vs. ontological, and weak vs. strong meanings of emergence is unhelpful in cracking this problem [e.g. Bedau 1997; Silberstein and McGeever 1999; Kim 2006; Clayton and Davies 2006].

As a matter of fact, every sociologist, even at the beginning of his/her career, knows the meaning of this debate very well. Therefore, I do not want to go into further detail on this. More important is that, recently, the respective positions have become less clear-cut than in the past.

First of all, advocates of methodological and ontological individualism now seem more inclined to take into account institutions and social structures as macro constrains upon individual action [Coleman 1990; Udehn 2001; Hedström 2005]. Institutions, in their formal and informal/regulative and constitutive meaning, e.g. the rules of the game, incentives embodied in the institutional setting, or the cognitive and cultural behavioural (and identity) frameworks of social actors, are all seen as the main features of the "social situation" that simultaneously constrain and make individual action possible [Scott 1995; North 2005]. Furthermore, following Boudon and Coleman, many sociologists attached to methodological and ontological individualism now try to understand the influence of social structure on individual behaviour and, in particular, the influence of position within the interaction context [Boudon 1984; Boudon 1992; Coleman 1990; Hedström 2005; Granovetter 2005]. Social institutions and social structures are therefore increasingly recognised also by supporters of methodological individualism.

Secondly, some macro-sociologists seem more inclined than in the past to recognise the need to combine macro societal analysis and generative mechanism-based explanations [Manzo 2007]. For instance, in his ambitious attempt to combine empirical research and theory, statistical macro sociology and the theory of individual action, Goldthorpe [2007, 16] emphasises that "the explanation of social phenomena is sought not in terms of the functional or teleological exigencies of social systems

but rather in terms of the conduct of individuals and of its intended and unintended consequences."

To sum up, while many advocates of individualism are trying to understand the macro-micro mechanisms that "situate" individual action sociologically, some macro-sociologists are trying to anchor their macro analyses onto micro generative processes. This paper argues that social simulation strengthens links and integrative frameworks, and "secularises" the debate. In fact, social simulation brings this debate away from a foundational and philosophical level to a more pragmatic one. In particular, social simulation allows us to identify particular mechanisms that can help map the micro-macro links in social systems. Some examples of this new approach will be discussed in the third section. Let us first introduce what social simulation exactly is.

2.   What is Social Simulation?

Social simulation is a relatively new field of research that developed over the nineties, when several milestones in the use of computer modelling tools were being recognised in social sciences. Many factors triggered this innovation. In brief, it is worth remembering the impact of *Growing Artificial Societies. Social Science from the Bottom-Up* by Epstein and Axtell [1996], *The Complexity of Cooperation. Agent-Based Model of Competition and Collaboration* by Axelrod [1997], two famous edited books on complex systems in economics by scholars of the Santa Fe Institute [Anderson, Arrow, and Pines 1988; Arthur, Durlauf, and Lane 1997], and of a good number of edited books on social simulation in many disciplinary fields, such as sociology, anthropology, history, demography and organization sciences [Gilbert and Doran 1994; Carley and Prietula 1994; Gilbert and Conte 1995; Conte, Hegselmann and Terna 1997; Sichman, Conte and Gilbert 1998; Prietula, Carley, and Gasser 1998; Ballot and Weisbuch 2000; Kohler and Gumerman 2000; Lomi and Larsen 2001]. In conjunction with this, a strong influence was exerted by two successful specialised journals, *Computational and Mathematical Organization Theory* and *JASSS-Journal of Artificial Societies and Social Simulation*, as well as by the founding of three representative associations including a vast number of computational social scientists (ESSA in Europe, NAACSOS in the United States, and PAAA in Pacific Asia), and the proliferation of social simulation conferences all over the world. Year after year, many reviews and books on social simulation have been published, also in mainstream journals, giving a vivid impression of the consistency now reached by this field [e.g. Macy 2002; Macy and Willer 2002; Gotts, Polhill and Law 2003; Billari and Prskawetz 2003; Sawyer 2004; Bousquet, Trébuil and Hardy 2005; Gilbert and Abbott 2005;

Epstein 2006; Tesfatsion and Judd 2006; Rennard 2007; Miller and Page 2007; Edmonds, Hernandez, and Troitzsch 2007; Matthews *et al.* 2007; Gilbert 2008].

As a definition, social simulation could be defined as *the study of social outcomes, let us say a macro regularity, by means of computer simulation where agents' behaviour, interactions among agents and the environment are explicitly modelled to explore those micro-based assumptions that explain the macro regularity of interest.* Computer simulation is used to model and to understand the generative process between assumptions on a micro-level (e.g. how agents behave, how they interact) and the consequences that agents' interactions bring about over time at a macro level of analysis.

At the core of social simulation, there is a new instrument and a new method. The instrument is agent-based modelling, that is, a computational tool to formalise models of social outcomes, such as urban segregation patterns or unemployment in labour market, by explicitly representing the agents, interactions and the (geographical, spatial, interaction, institutional) environment involved [Miller and Page 2007; Gilbert 2008]. This instrument allows social scientists to grasp within a formalised model those relevant features of the complexity of social systems, such as autonomy and heterogeneity of agents, bounded and adaptive rationality, space and local interactions, and non-equilibrium dynamics which are analytically intractable with mathematical or statistical models [Squazzoni and Boero 2004; Miller and Page 2007]. Using the computer as a "virtual laboratory" to conduct "virtual experiments" allows social scientists to work with "generative models" of social outcomes. To put it in Epstein's words:

> 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 is based on sound empirical grounds and the simulation results are stable and robust against simulation parameters, then the micro-specifications in question are said to satisfy the criterion of "generative sufficiency" as regards to the macro-regularity of interest. Again according to Epstein, "this demonstration [that is, *being able to generate a macro regularity of interest with an agent-based model*] is taken as a necessary condition for

explanation itself" [*ibidem*, 8]. According to the social simulation approach, explaining means generating that is, specifying and showing the generative process through which interacting agents in a given environment combine to produce the macro-regularity of interest.

Let us suppose that a social scientist would like to explain a macro outcome k_r. He/she would build an agent-based social simulation model of k_r because k_r is considered a complex outcome, not completely understandable either by direct observation or by using other modelling tools such as mathematical or statistical models. Let us suppose that A, B, C…, are components of the model that are introduced to understand k_r. They could be as follows: numbers and types of agents, rules of behaviour followed by agents, the interaction structure (how agents interact), and the constraints that characterise the macro-situation. Let us suppose that A_1, A_2, A_3…, B_1, B_2, B_3…, and C_1, C_2, C_3…, are all the possible variations that the components could in principle take. The generative experiment lies in exploring which of these variations of components A, B, C…, generate k_a, that is, the simulated outcome that should be compared to k_r. The generative principle is that if, A_2, C_1, D_3, N_5 allow us to generate $k_a = k_r$, then A_2, C_1, D_3, N_5 are sufficient generative conditions of k_r. These conditions have therefore explanatory power on k_r.

In cases of "multiple realizability," that is, in which not only A_2, C_1, D_3, N_5 but also other assumptions generate k_a [Sawyer 2005] and in general, identify not only the *sufficient* but also the *necessary* generative conditions, it is essential to turn to empirical data and analyses [Boero and Squazzoni 2005]. It is only by empirically calibrating a model and by introducing empirical evidence and data that a social scientist can keep these contingencies and contextual factors under control that are often crucial to explain a social outcome.

3.   Views on the Micro-Macro Link in Social Simulations

Social simulation models are especially targeted to analyse complex social outcomes, that is, macro outcomes that strongly depend on systemic processes of interactions between agents that are co-located within a given environment [Miller and Page 2007]. Every social simulation model is aimed at both or one of the following explanatory purposes: *a)* understanding how local patterns emerge and how they generalise across a social system; *b)* understanding how macro patterns and individual action influence each other over time. In both cases, the micro-macro link is a hard nut to crack.

In social simulation, understanding the micro-macro link requires grasping emergent properties, that is, "stable macroscopic patterns arising from the local interaction of agents" [Epstein and Axtell 1996, 35]. These properties have two meanings that I have explained below. Rather than being merely theoretical constructions, these meanings refer to clear-cut model-grounded concepts.

The first concept is the so-called *first-order emergence*. A first-order emergent property is a macro level property, i.e. a macro pattern, behaviour, structure or dynamic, that is generated through decentralised and localised interaction among agents. It is said to be emergent in regards to the decentralised and local interactions that are responsible for it, because it is not possessed by any agent in particular, but by the system as a whole. This means that this property can be understood only from the observer's perspective, referring to aggregate concepts that were not previously introduced into modelling the agents' behaviour. Moreover, it is emergent because this property is a global unplanned consequence of local interactions. It is worth emphasising that these emergent properties do not have an ontological meaning in themselves. They are studied because they arise from agents' interactions, and they can be understood only by dissecting these interactions. Examples of these models will be given in the next section.

The second is the concept of *second-order emergence*. A macro property is a second-order property if it is cognitively recognised by agents that have yielded it and if, as a consequence, it can be intentionally supported, maintained, changed or contrasted by the same agents that yielded it. In the previous type of models, agents interact locally and their behaviour changes under the pressure of local constraints. Agents are not aware of what they generate at a macro level. In this second type of models, the macro level feeds back directly onto the micro level. For this purpose, the model must be based on the presence of reflexive agents endowed with the cognitive capability of recognising the macro features of the system in which they are embedded, as well as the macro consequence of their actions. What is being studied in these models is the diachronic influence between the micro and the macro level, not just the macro outcomes of agents' interactions. These macro-micro feedbacks can operate through cognitive (e.g. inferences of individual agents) or institutional scaffolds (e.g. norms, structures, or institutional matrixes). While the first type of models deals with the link between simple components at the micro and complex dynamics at the macro, models of the second type add a further level of complexity at a micro level by introducing intentionality and cognitive properties inside the agents' behaviour [Gilbert 1996; Conte *et al.* 2001; Boero, Castellani, and Squazzoni 2004a; Boero, Castellani, and Squazzoni 2008].

To conclude, it is worth clarifying that each social simulation model, concerned with both first-order and second-order emergence, comprises a Coleman-like macro-micro-macro link [Coleman 1990]. Simulations are initialised with agents located in an environment with given macro constraints (e.g. a given space distribution of agents, a given position in a network, or a heterogeneous distribution of resources). Since most social simulation models do not assume fixed rules at the micro level, but adaptation and agent learning, this means that the aggregate effect of interactions changes the behaviour at a system level (e.g. a change in the initial space distribution of agents, or a change in the prior position of agents in the network) and this always has an *ex-post* impact on the agents' behaviour in the following interactions (e.g. by providing incentives for a change in behaviour). The difference between first and second-order emergence models lies in the mechanisms of macro-micro-micro change, mediated by local adaptations in the former and by reflexivity in the latter.

4.   Examples

Most social simulation models deal with first-order emergence. In this case, as we have mentioned, we deal with how interactions among agents combine to generate stable collective patterns over time. This tradition originates from seminal work on residential segregation by Schelling [1971; 1972; 1978] and on collective behaviour by Granovetter [1978], subsequently elaborated in Granovetter and Soong [1986; 1988].

Schelling's and Granovetter's models exemplarily demonstrated two important principles that were strengthened in subsequent social simulation models becoming now sound and well-recognized arguments: *a*) the explanation of a social outcome is more informative when it can address how individual motivation and behaviour give rise to social patterns rather than assuming that they are determined by other macro variables or are simple aggregates of individual characteristics; *b*) the focus on the explicit modelling of agents' interaction allows us to map micro-macro linkages so that what seems to be at first sight a strange, surprising and counter-intuitive collective social outcome can be explained in terms of interactions and of particular aggregation processes. Granovetter and Soong summarised the novelty of these models as follows:

> These models have three distinct advantages over most current models: 1) their treatment of dynamics is explicit and central (i.e. they do not deal in comparative statistics), 2) they make no assumption of linear relations among variables, and 3) they are driven not by correlations but by well-defined causal mechanisms. We see models of this kind as part of a broader movement in sociology toward explicit, concrete, dynamic analysis and away from the general linear model, which, assuming

that the size of causes must determine the size of consequences, prepares us poorly for the many surprises that social life has in store [Granovetter and Soong 1988, 103].

Now, let me just summarise the main constituents of these standard models.

As is well known, Schelling's purpose was to illustrate the dynamics of residential mobility and segregation by race and ethnics, i.e. a long lasting pattern of many large cities in the US. In his simple and abstracted model, first elaborated by placing black and white pieces on a chessboard, he showed that individual preferences about where to live combine in aggregate spatial patterns of residential segregation. Schelling demonstrated the power of interdependence mechanisms to explain micro-macro links.

The first version of the model is based on a rectangular grid of 16*13 cells, which represents an idealised urban space. In this space, cells represent a home-site that can be occupied by one of the 138 households, black or white, with about a quarter of the cells that are empty. Thus, there are $3^{(16 \times 13)} = 3^{208} \approx 10^{99}$ possible states of the system, each of which represents one housing pattern distribution of black and white households [Casti 1994, 213]. 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.

Granovetter's model of collective behaviour has followed Schelling's footsteps by further abstracting this threshold-based tipping point mechanism. His applications include many social situations in which agents are called to take a binary decision. Unlike Schelling and his focus on spatial relations, Granovetter explicitly introduces the assumption that individual behaviour depends in part on the composition of the whole system of individuals who have already made a choice. In doing

this, Granovetter explicitly introduces a macro social property that influences individual action.

A simple version of the model is based on 100 agents distributed in a space that are called to take a binary decision (e.g. to join or not to join a riot) following an individual threshold, i.e. the proportion of the group he/she would have to see join before he/she would do so. The threshold is distributed from 0 to 100. Agents are heterogeneously distributed between "radicals" (low threshold and high benefit of rioting), "instigators" (people who riot even when no one else does) and "conservatives" (high threshold and low benefit of rioting). To simplify this means that agent *x = threshold 0* will decide to riot regardless of what others decide, the *agent y = threshold 1* will follow *x*, *agent z = threshold 2* will follow *y* and so on until the hundredth agent. Agent *x*, the so-called "instigator," will cause a riot. This is a linear link between micro behaviour and macro outcomes called "domino" or "bandwagon" effect. The proportion of outcomes is linearly related to the proportion of causes towards attaining the equilibrium (100 agents who riot). Now, let us suppose removing *agent y = threshold 1*. The consequence will be to nip the riot in the bud, that is, a completely different outcome at a macro level from a small difference at the micro. This confirms how much "it is hazardous to infer individual dispositions from aggregate outcomes" [Granovetter 1978, 1425]. Granovetter then assumes an average threshold distribution in the population and introduces the tendency of agents to weigh others' decisions differently depending on friendship. This is to introduce social influence on rational individual action, which is an important constituent of the social structure. Let us assume that the influence of the decision of a friend counts twice that of strangers. Let us suppose that, in a population of 100 agents, agent *w =* threshold 50 faces a situation of 48 rioters and 52 non-rioters. In this case, agent *w* will decide not to riot. Let us now assume, however, that agent *w =* threshold 50 is a node of a friendship network of 20 agents, 15 of which have already decided to riot. According to the assumption on the friends' decision, now agent *w* will not "see" the group as composed of 48 rioters and 52 non-rioters but by [(15*2) + (33*1)] rioters and [(5*2) + (47*1)] non-rioters, that is, by 63 rioters on 120, with a threshold on .525, higher than .50. The result will be that agent *w* will decide to join the riot.

In these pioneering simulation studies, Granovetter shows how constituents of social structure can affect the link of micro motivations and macro social outcomes. When equilibria at a macro level are unstable with no chance of mapping micro and macro levels through a deterministic solution, the effects of social structure may overwhelm those of individual preferences. This evidence emphasises the importance of understanding the "situation-specific" aggregation processes. To put it in Granovetter's words:

> 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 [*ibidem*, 1442].

Granovetter's model is an eminent example of a really vast category of models that have focused on opinion dynamics, minority games, critical mass, innovation diffusion, social contagion, domino and bandwagon effects, giving rise to abundant research also in social simulation with very interesting applications [e.g. Hedström 1994 on social movements, Picker 1997 on crime, Mayer and Brown 1998 on voting, Weisbuch *et al.* 2002 and 2005 and Deffaunt *et al.* 2002 on opinion dynamics, Cederman 2003 on civil wars, Hedström 2005 on unemployment, and Epstein 2006 on retirement]. This literature has recently enjoyed a degree of popularity also because of the success of some good popular books [e.g. Gladwell 2001; Ball 2004]. Segregation models inspired by Schelling have become a vigorous stream in social simulation literature in itself as well. This corroborates the evidence that formalised models encourage the cumulativeness of scientific progress.

Epstein and Axtell [1996], for example, have worked on variants of the standard Schelling model. They introduced a Von Neumann neighbourhood (4 agents), a 50*50 lattice with 2000 households, 20% of the sites vacant, more tolerant thresholds in individual preferences (preference from 50% to 25% of households of the same group in the same neighbour), different movement rules, and a finite lifetime for households. The results confirm that even a little racism is enough to tip a society into a segregated pattern. Bruch and Mare [2006] investigated how much the micro-macro mapping of the Schelling standard version depends on the assumption of threshold behaviour at the micro level. They show that continuous function preferences at a micro level, allowing households to adapt to neighbourhood composition and change continuously, can soften the segregation patterns at the macro level. As a consequence, they argue that residential tipping is heavily model-dependent. Moreover, they suggest empirically validated simulations of their segregation model. Other variants were explored by Pancs and Vriend [2003], who introduced households with preferences toward integration and deliberate refusal of segregation. Laurie and Jaggi [2003] studied the effect of the enlargement of the space vision of households. Gilbert [2002] modified the standard version to introduce second-order emergent properties. Considering its interest, we will return on this last variant later.

Another interesting sociological example of stream on first-order emergence approach is the analysis of the emergence of institutions. How does a population of heterogeneous localised interacting agents generate institutional equilibria at a macro level? How do institutions emerge from agents' interaction and persist over time? Recently, two brilliant and simple examples are Epstein's model of social norms and Hodgson's model of the emergence of conventions [Epstein 2001; Hodgson and Knudsen 2004].

Epstein's model aims to understand the relation between the strength of a social norm and the weight of agents' calculating efforts to grasp fundamental evidence of the social life according to which, once a norm is entrenched, individuals tend to conform thoughtlessly. This model is based on agents who are able to learn how to behave and, most importantly, how much to think about how to behave. The model consists of a ring where 191 agents are randomly localised. Agents can decide to adopt a norm x or a norm y based on the observation of what others do in a given sampling radius that may be heterogeneous among agents and may change over time. Agents behave like "lazy statisticians" calculating the relative frequency of the two norms in their radius and deciding whether to confirm, reduce or enlarge their sampling radius if sampling results are similar or different to what was obtained before (if results are different, the sampling radius is increased, confirmed if results are identical and reduced if the reduction of the sample does not change results). The decision horizon (sampling radius) therefore continuously and adaptively changes at an individual level. After this, agents simply decide to adopt the norm which is the majority in their sampling radius. Finally, noise is introduced by allowing some probability that an agent adopts a norm randomly.

Epstein gives results from seven simulation settings, where all simulation parameters are modified and tested, such as the number of norms, noise level, and size of the sampling radius. The simulation spectrum is between a first static and deterministic one-solution setting (a single norm and no noise) and a last totally chaotic one (two norms, highest possible noise level). Simulation results show a regionalisation of space, with local conformity and global diversity mechanisms that follow a punctuated equilibrium macro pattern. While agents converging on norms reduce the amount of their calculating effort, by reducing the size of their sample radius, the agents that are stuck in the middle of the two regions where norms respectively diffuse must make a cognitive effort to continuously explore and change their sampling radius. The results, here just briefly summarised, make it feasible that individual calculating effort is often inversely related to the strength of a social norm.

Following a similar inspiration, Hodgson and Knudsen [2004] focused on the emergence of convention, in this case the side of the ring on which to drive, by ex-

ploring the role of bounded rationality and habit. The model consists of 40 agents driving around a 100x2 grid arranged in a ring with 2 lanes and 100 zones. Agents are randomly assigned to positions and must decide whether to drive on the right or the left side of the ring, depending on local information about traffic, and must try to avoid accidents. Each agent is characterised by five cognitive and behavioural dispositions that influence his/her behaviour. These dispositions determine how the agent calculates information (e.g. space, the position of others) and how he/she is more or less inclined towards habituation. Colliding agents are replaced, keeping the number of agents in the system constant. Therefore, agents have a bounded rationality, are heterogeneous and adaptive, have a local vision, interact, and follow backward looking strategies of behaviour.

Simulation outcomes show that a convention emerges according to a path-dependent cumulative pattern highly sensitive to initial conditions, that habituation alone does not allow the emergence of robust patterns (since convergence can emerge also without habits), but that habituation reduces the impact of other potentially relevant factors like errors, collisions, and local heterogeneity. As shown in Figure 1, habituation is of great importance in different parameter spaces, writing off the effect of errors. To further corroborate this evidence, Hodgson and Knudsen create other simulation settings where inertia and larger decision horizons are tested. In the second case, agents are less boundedly rational, since now they are capable of processing more detailed information and of considering more information sources. The evidence is twofold. Firstly, it is seen that as a convergence begins to emerge in the population, more and more surviving agents develop a habit consistent with conventions arising out of interaction. Secondly and more important, habit could be viewed as an effective institutional scaffold particularly when agents are boundedly rational, the situation is more uncertain, and the decision horizon is limited, as it is shown in Table 1.
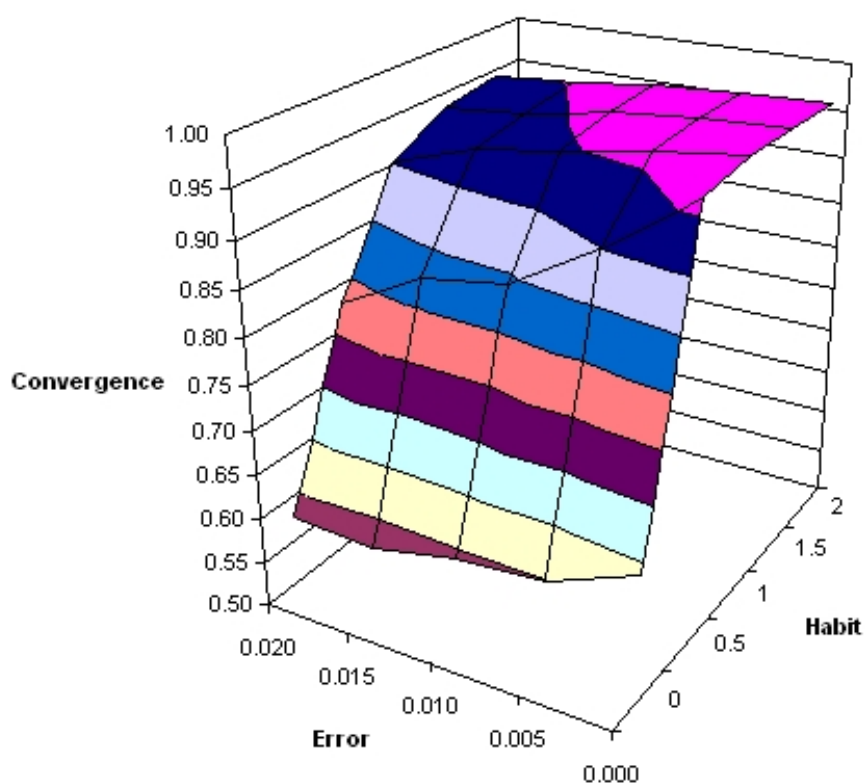
FIG. 1. The degree of institutional convergence by habit and error. The higher the value of convergence in the vertical axis, the stronger is the institutional convergence of the population. The evidence is that a growth in the value of habit in the horizontal axis implies the strongest institutional convergence and writes off the impact of error [Hodgson and Knudsen 2004].

TAB. 1. *The degree of institutional convergence by decision horizon*

	Degrees of Convergence		
Decision Horizon	wHabit = 0	wHabit = 1	Weigh of the habit effect
0	0.50	0.53	0.03
5	0.51	0.80	0.30
10	0.56	0.88	0.32
15	0.69	0.95	0.26
20	0.85	0.98	0.13
25	0.94	0.98	0.04
30	0.98	0.98	0.00
50	0.99	0.99	0.00
100	0.98	0.98	0.00

Note: The habit effect is a t-test of the difference between presence/absence of habit. Each value was tested on 360 simulation runs and averaged on 30 samples [Hodgson and Knudsen 2004].

Examples of second-order emergence models are less abundant but no less important. As already mentioned, these models have the prerequisite of adding more sophistication to the design of the micro level towards reflexivity and other human cognitive properties. In this vein, Gilbert [2002] worked some modifications into the standard Schelling segregation model by introducing second order properties, while at the same time keeping the model as simple as possible.

Gilbert first replicated the standard version of the model. Space is characterised by a grid of 500 x 500 square patches where 1,500 agents are distributed, with a majority of "greens" and a minority of "reds." Gilbert uses this first simulation setting as a basis for testing small variants and then introduces two important factors that could lead to second-order properties. First, he introduces a typical macro-level effect that can influence or constrain individual action, i.e. the crime rate. He assumes that the cost of a home in each possible neighbourhood depends in part on the local crime rate that depends on the ratio of agents localised there (e.g. the redder it is the higher the crime rate). He assumes that instead of choosing new locations at random, agents can only move to spots where they can afford to buy or to rent. This is to add a macro constraint, that is, a relation between the value of the new and the old locations. As it is shown in Figure 2, the result of the simulation is a well structured clustering of agents, with poor reds confined to poorest neighbourhoods and richer greens who aggregate around desirable areas. Then, he adds an explicit second-order property, i.e. the capability of agents to "detect the presence of emergent features and act accordingly." In this simulation, agents may label the patches as red or green according to past history of patches and may recognize which patch is good for them. For example, we could make the analogy of the emergence of the good or bad "image" of particular areas and the effect that this image can have on residential decision of a household. Again, as shown in Figure 2, the simulation outcomes show a strong clustering of space, i.e. a macro dynamic similar to that which Schelling derived in his standard model.

According to the well known argument on "multiple realizability" of society features, these simple simulations demonstrate that very different micro assumptions can generate the same macro outcomes. The consequence of this is that empirically discriminating the behaviour of individuals at a micro level is particularly needed to shed light on macro social features.
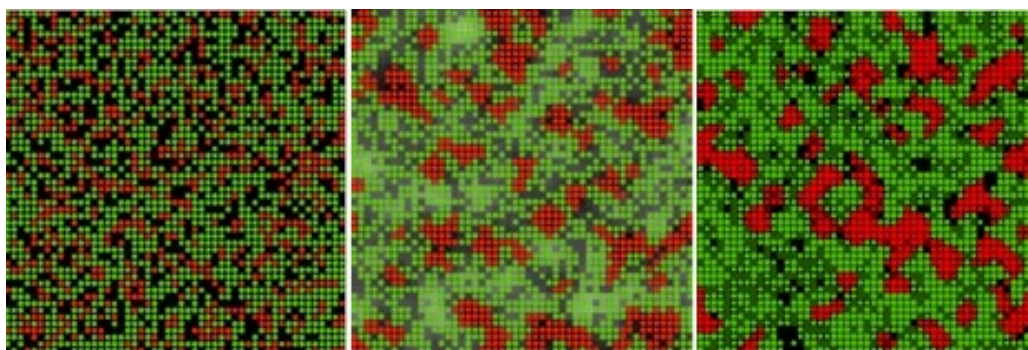
FIG. 2. Spatial distribution patterns in the initial random distribution of 1,500 agents on the top-left; spatial patterns in "crime rate simulation setting," on the top-right, and in the "second-order emergence simulation setting," below [Gilbert 2002].

Conte and Paolucci [2003] investigated the relevance of reputation for the emergence and maintenance of social order. They wanted to show how cognitive evaluations of agents can become social knowledge artefacts that are distributed across the social environment and can be used by agents to detect attitudes so to reduce the risk of encountering cheaters. The authors start with a simplified model, where free-riders and normative agents interact in a competitive space. Then, they add step-by-step cognitive sophistications to the agents' behavioural architecture. The more the agents are endowed with cognitive capabilities of elaborating information and using the social environment as a knowledge repository, the more the social system is able to protect and maintain social norms. In their simulation models, the social knowledge produced by agents, as in the case of gossip, becomes a property of the social environment, not of individual agents, following interesting second-order emergent dynamics more or less robust against micro-level variations.

This same inspiration was followed by Hales [1998] who has studied the emergence of stereotypes in social groups in repeated Prisoner's Dilemma games, and by Doran [1998], who studied the emergence and reproduction of misbelief in social groups. Unlike the countless examples of evolutionary game theory agent-based models, in which feedback from macro to micro is embodied in payoff matrixes or in evolutionary selection mechanisms that happened "behind the backs of the agents" [e.g. Axelrod 1997; Cohen, Riolo, and Axelrod 2001; Bowles and Gintis 2004], in these models the macro-micro feedback is endogenously internalised by the cognitive capability of agents to generate "mental representations" of the evolved macro structures [Hales 1998]. This is what we have previously called "second-order emergence."

For example, in the field of economic sociology, together with Boero and Castellani, the author worked on a different version of a model of industrial districts to

investigate how different behavioural heuristics toward partners' selection of firms located in an industrial district can influence the technology and market adaptation capability of the system as a whole. In a first version, we assumed simple behavioural rules with which final firms selected their sub-contracted production partners under the pressure of technology innovation and market demand. In the first simulation setting, firms followed an optimal rational strategy under given constraints, trying to get the best partner available in every production cycle. In the second simulation setting, firms follow a *satisfacing* strategy, holding their partners until profit on market grows or is average. The results is that one-shot optimisation at a micro level causes lower capability of the system in adapting to technology innovation and market demand, whereas stability of inter-firm relations allows firms to improve coordination and technological learning at a level of production chains [for details see Squazzoni and Boero 2002]. In a second version, we enriched the cognitive properties of industrial district firms' behaviour. Firms were now endowed with capabilities of recognising and typifying the social and competitive context in which they were embedded, even if under the principles of bounded adaptive rationality. The more the agents are confident of their perceptions (e.g. on production partners, technology and market challenges), the more these perceptions are supported by empirical evidence, and the more they put trust on themselves and on others, the more they behave a group-like attitude. The simulation outcomes show that when a group-like attitude gains ground, the system achieves more robust market and technology performance [for details see Boero, Castellani, and Squazzoni 2004a; Boero, Castellani, and Squazzoni 2004b]. This evidence has been recently found in a more simplified and abstracted model of interaction among agents in a social interdependence environment. Efficiency at the micro level and welfare at the macro level combined particularly when agents were provided with more sophisticated socio-cognitive properties [Boero, Castellani, and Squazzoni 2008].

5. Concluding Remarks

Social simulation is the supporting arm of a generative sociology able to dissect those social mechanisms that are responsible for many peculiar, unpredictable, unplanned, and unintended features of social life. It gives way to a sociology that is able to understand crucial social outcomes by carefully dissecting the mechanisms behind their onset using formalised models, such as simulation models and in particular agent-based ones, which can help the sociologist to explore assumptions and keep control of their consequences in a cumulative and rigorous way. Unlike highly

abstract and general mathematical models, by using agent-based models, a sociologist can work with formalised models without giving up realism [Troitzsch 1997].

Formalising models is a pre-requisite to illuminate social mechanisms. Computer simulation is of paramount importance for discovering and exploring social mechanisms, their validity domain, and their hidden consequences at a low cost, that is, within "virtual laboratories." This paper attempts to tighten connections between the method and tools of social simulation and the approach and the targeting of analytical sociology [Hedström 2005]. Analytical sociology can offer a guide to theory building and a style of explanation, while social simulation can offer modelling tools, good methodological practices, and cumulative experiences.

So far, social simulation scientists have identified certain powerful explanatory mechanisms that can be applied to many spheres of social and economic life [Barbera and Negri 2005]. A first family of mechanisms assembles all the examples of micro-macro diachronic linkages, as in Granovetter's and his many followers. Threshold and tipping points, path dependence and increasing returns, externalities and positive feedbacks are all examples of building blocks of mechanisms in which the micro-macro mapping is driven by diachronic changes that strengthen, amplify or reverse emergent patterns and particular equilibrium solutions within social systems. A second family assembles all the examples of micro-macro spatial linkages, where space is not intended simply as a geographical feature but rather as a representation of interaction forms [Cederman 2005]. The many models of contagion/diffusion dynamics, opinion and culture dynamics are all examples of building blocks of mechanisms that allow us to study the emergence of social patterns at a local level and their spread across systems at a global level, as well as the persistence of (cultural, political, social) difference and heterogeneity in social systems. It is worth noting that these two "families" have significant mutual connections, given the unyielding space-time dimension of social life [Elias 1984].

The point is that complexity typical of many social situations, such as micro-heterogeneity and decentralised and localised interactions, do not engender deterministic linear solutions of micro-macro links. Aggregation is not linear, is not a simple projection of micro instances, cannot be statistically averaged and can not be reduced to any representative behaviour postulated at a micro level. The only serious means to understand the generative consequence of these sources of complexity on macro social patterns is by modelling assumptions on agents and interactions and studying implications at a macro level through computer simulation.

To conclude, there are many lessons that a sociologist can draw from social simulation, as well as many critical points on which to improve our confidence in the future.

Firstly, social simulation allows us to emphasise the need to deepen our basic understanding of the behaviour of individuals in social settings for action-based explanations of social outcomes [Hedström 2007]. Given the already established connection with behavioural and experimental sciences, most social simulation models draw sociologists toward the need for a better-constructed theory of human behaviour, that is not only confined to a rational choice paradigm [e.g. Gintis *et al.* 2005]. Unlike game theory and rational choice models, in social simulation models it is assumed a low level of intelligence and rationality of agents. Agents are often modelled as boundedly rational agents, affected by information asymmetries, and subjected to the strength of social influences and norms. The problem of how far we should push the intelligence of agents in our models to shed light on social outcomes is still under investigation [Miller and Page 2007]. For this purpose, the difficult task is to find the appropriate level of sophistication of agents between the extreme simplification of folk psychology and the highly complicated artificial intelligence architectures suggested by cognitive scientists [Gilbert 2005; Squazzoni 2007]. However, the demonstration of the relevance of micro-sided sociological models is a first relevant contribution of social simulation studies.

Secondly, social simulation models demonstrate the explanatory power of interaction structures and forms to understand micro-macro links. Interaction among agents is at the core of any social outcome. Each model with a sociological purpose should include interaction among agents as its main building block. This brings us back to the task of finding what kind of resources agents exchange or compete for in social settings that was at the core of social exchange theory [Granovetter 2005]. Some simulation models have started to answer this question, such as the many trust and reputation models [Sabater and Sierra 2005]. For a supporter of action-based explanations the point is not just to map interaction forms and derive conclusions about sociological mechanisms, as network analysts do, but rather to understand how particular interaction structures and forms intervene to mould the links between micro motivations and macro consequences.

These arguments draw attention to the problem of how to collect data and measures that can help the modeller calibrate simulations, and how to use data to validate simulation outcomes. Concerning the relation between data and theoretical models, some steps have been made in social simulation, as the current plentiful methodological debate testifies to [e.g. Boero and Squazzoni 2005; Moss and Edmonds 2005; Fagiolo, Moneta, and Windrum 2007; Moss 2008].

To return to the main issue of this paper, although social simulation still needs to make a great deal of progress, it includes a pragmatic approach to the old dispute on the micro-macro link that can foster connections and collaboration between dif-

ferent perspectives and avoid often useless ontological discussions. At this point, the ground is fertile enough for scholars to put these pieces in order and to classify concepts, models, and evidence to foster improvements for the analytical toolkit of the Twenty-first century sociologist.

References

Alexander, J.C., Giesen, B., Münch, R., and Smelser, N.J. (Eds.)
1987   *The Micro-Macro Link*. Berkeley: University of California Press.

Anderson, P.W., Arrow, K.J., and Pines, D. (Eds.)
1988   *The Economy as an Evolving Complex System*. Santa Fe Institute Studies in the Science of Complexity. Reading, MA: Addison-Wesley.

Archer, M.S.
1995   *Realist Social Theory: The Morphogenetic Approach*. New York: Cambridge University Press.

Arthur, B.W., Durlauf, S.N., and Lane, D. (Eds.)
1997   *The Economy as an Evolving Complex System II*. Santa Fe Institute Studies in the Science of Complexity. Reading, MA: Addison-Wesley.

Axelrod, R.
1997   *The Complexity of Cooperation. Agent-Based Models of Competition and Collaboration*. New Jersey: Princeton University Press.

Ball, P.
2004   *Critical Mass. How One Thing Leads to Another*. London: Arrow Books.

Ballot, G., and Weisbuch, G. (Eds.)
2000   *Applications of Simulation to Social Sciences*. Oxford: Hermes Sciences Publications.

Barbera, F., and Negri, N.
2005   "La connessione micro-macro. Azione-aggregazione-emersione." Pp. 93-112 in *La spiegazione sociologica. Metodi, tendenze, problemi*, edited by M. Borlandi and L. Sciolla. Bologna: Il Mulino.

Bedau, M.
1997   "Weak Emergence." *Philosophical Perspectives* 11: 375-399.

Billari, F., and Prskawetz, A. (Eds.)
2003   *Agent-Based Computational Demography. Using Simulation to Improve Our Understanding of Demographic Behaviour*. Berlin Heidelberg: Springer Physica-Verlag.

Boero, R., Castellani, M., and Squazzoni, F.
2004a   "Cognitive Identity and Social Reflexivity of the Industrial District Firms. Going beyond the 'Complexity Effect' with an Agent-based Computational Prototype." Pp. 48-69 in *Regulated Agent-Based Social Systems*, edited by G. Lindemann, D. Moldt, and M. Paolucci. Berlin Heidelberg: Springer Verlag, 48-69.

2004b "Micro-Behavioural Attitudes and Macro Technological Adaptation in Industrial Districts. An Agent-Based Prototype." *Journal of Artificial Societies and Social Simulation* 7: http://jasss.soc.surrey.ac.uk/7/2/1.html.

2008   "Individual Behavior and Macro Social Properties. An Agent-Based Model." *Computational and Mathematical Organization Theory* 14: 156-174.

Boero, R., Squazzoni, F.

2005   "Does Empirical Embeddedness Matter? Methodological Issues on Agent-Based Models for Analytical Social Science." *Journal of Artificial Societies and Social Simulation* 8: http://jasss.soc.surrey.ac.uk/8/4/6.html.

Boudon, R.

1984   *La place du désordre. Critiques des théories du changement social*. Paris: Presses Universitaires de France.

1992   "Action." Pp. 21-55 in *Traité de sociologie*, edited by R. Boudon. Paris: Presses Universitaires de France.

Bousquet, F., Trébuil, G., and Hardy, B. (Eds.)

2005   *Companion Modeling and Multi-Agent Systems for Integrated Natural Resource Management in Asia*. Metro Manila, Philippines: IRRI.

Bowles, S., and Gintis, H.

2004   "The Evolution of Strong Reciprocity. Cooperation in Heterogeneous Populations." *Theoretical Population Biology* 132: 337-356.

Bruch, E., and Mare, R.D.

2006   "Neighborhood Choice and Neighborhood Change." *American Journal of Sociology* 112: 667-709.

Carley, K.M., and Prietula, M. (Eds.)

1994   *Computational Organization Theory*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Casti, J.

1994   *Complexification. Explaining a Paradoxical World Through the Science of Surprise*. Hillsdale, NY: Harper Collins Publishers.

Cederman, L.-E.

2003   "Modeling the Size of Wars: From Billiard Balls to Sandpiles." *American Political Science Review* 97: 135-150.

2005   "Computational Models of Social Forms: Advancing Generative Process Theory." *American Journal of Sociology* 110: 864-893.

Clayton, P., and Davies, P. (Eds.)

2006   *The Re-Emergence of Emergence The Emergentist Hypothesis from Science to Religion*. Oxford-New York: Oxford University Press.

Cohen, M.D., Riolo, R.L., and Axelrod, R.

2001   "The Role of Social Structure in the Maintenance of Cooperative Regimes." *Rationality and Society* 13: 5-32.

Coleman, J.

1990   *Foundations of Social Theory*. Cambridge, MA: The Belknap Press of Harvard University Press.

Conte, R., Edmonds, B., Scott, M., and Sawyer, R.K.

2001　"Sociology and Social Theory in Agent-Based Social Simulation: A Symposium." *Computational and Mathematical Organization Theory* 7: 183-205.

Conte, R., Hegselmann, R., and Terna, P. (Eds.)

1997　*Simulating Social Phenomena*. Berlin Heidelberg: Springer Verlag.

Conte, R. and Paolucci, M.

2003　*Reputation in Artificial Societies. Social Beliefs for Social Order*. Dordrecht: Kluwer Academic Publishers.

Deffaunt, G., Amblard, F., Weisbuch, G., and Faure, T.

2002　"How can Extremism Prevail? A Study Based on the Relative Agreement Interaction Model." *Journal of Artificial Societies and Social Simulation* 5: http://jasss.soc.surrey.ac.uk/5/4/1.html.

Doran, J.

1998　"Simulating Collective Misbelief." *Journal of Artificial Societies and Social Simulation* 1: http://jasss.soc.surrey.ac.uk/1/1/3.html.

Edmonds, B., Hernandez, C., and Troitzsch, K.G. (Eds.)

2007　*Social Simulation: Technologies, Advances and New Discoveries*. Hershey, NY: Information Science Reference.

Elias, N.

1969　*The Court Society*. New York: Pantheon.

1970　*What is Sociology*. Princeton: Princeton University Press.

1984　*Time: An Essay*. London: Blackwell.

Epstein, J.M.

2001　"Learning to Be Thoughtless: Social Norms and Individual Computation." *Computational Economics* 18: 9-24.

2006　*Generative Social Science. Studies in Agent-Based Computational Modeling*. Princeton: Princeton University Press.

Epstein, J.M., and Axtell, R.

1996　*Growing Artificial Societies. Social Science from the Bottom-Up*. Cambridge, MA: MIT Press.

Fagiolo, G., Moneta, A., and Windrum, P.

2007　"A Critical Guide for Empirical Validation of Agent-Based Models in Economics: Methodologies, Procedures, and Open Problems." *Computational Economics* 30: 195-226.

Giddens, A.

1986　*The Constitution of Society. An Outline of a Theory of Structuration*. Berkeley: University of California Press.

Gilbert, N.

1996　"Holism, Individualism and Emergent Properties. An Approach from the Perspective of Simulation." Pp. 1-27 in *Modelling and Simulation in the Social Sciences from the Philosophy Point of View*, edited by R. Hegselmann, U. Mueller, and K.G. Troitzsch. Dordrecht: Kluwer Academic Publishers.

2002   "Varieties of Emergence." Pp. 41-56 in *Social Agents: Ecology, Exchange, and Evolution. Agent 2002 Conference*, edited by D. Sallach. Chicago: University of Chicago and Argonne National Laboratory.

2005   "When Does Social Simulation Need Cognitive Models?" In *Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation*, edited by R. Sun. Cambridge: Cambridge University Press.

2008   *Agent-Based Models*. London: Sage.

Gilbert, N., and Abbott, A.

2005   "Introduction." *American Journal of Sociology* 110: 859-863.

Gilbert, N., and Conte, R. (Eds.)

1995   *Artificial Societies: The Computer Simulation of Social Life*. London: UCL Press.

Gilbert, N., and Doran, J. (Eds.)

1994   *Simulating Societies. The Computer Simulation of Social Phenomena*. London: UCL Press.

Gintis, H., Bowles, S., Boyd, R., and Fehr, E. (Eds.)

2005   *Moral Sentiments and Material Interests*. Cambridge, MA: MIT Press.

Gladwell, M.

2001   *Tipping Point. How Little Things Can Make a Big Difference*. London: Abacus.

Goldthorpe, J.H.

2007   *On Sociology. Volume One: Critique and Program*. Stanford: Stanford University Press.

Gotts, N.M., Polhill, J.G., and Law, A.N.R.

2003   "Agent-Based Simulation in the Study of Social Dilemmas." *Artificial Intelligence Review* 19: 3-92.

Granovetter, M.

1978   "Threshold Models of Collective Behavior." *American Journal of Sociology* 83: 1420-1443.

1985   "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91: 481-510.

2005   "The Impact of Social Structure on Economic Outcomes." *Journal of Economic Perspectives* 19: 33-50.

Granovetter, M., and Soong, R.

1986   "Threshold Models of Diffusion and Collective Behavior." *Journal of Mathematical Sociology* 9: 165-179.

1988 "Threshold Models of Collective Behavior: Chinese Restaurants, Residential Segregation, and the Spiral of Silence." *Sociological Methodology* 18: 69-104.

Hales, D.

1998   "Stereotyping, Groups and Cultural Evolution: A Case of 'Second-Order Emergence'?" Pp. 140-155 in *Multi-Agent Systems and Agent-Based Simulation. First International Workshop, MABS '98. Proceedings*, edited by J.S. Sichman *et al.* Berlin-Heidelberg: Springer Verlag.

Hedström, P.

1994   "Contagious Collectivities: On the Spatial Diffusion of Swedish Trade Unions, 1890-1940." *American Journal of Sociology* 5: 1157-79.

2005   *Dissecting the Social. On the Principles of Analytical Sociology.* Oxford: Oxford University Press.

2007   "Actions and Networks: Sociology that Really Matters... to Me." *Sociologica* 1. doi:10.2383/24187

Hodgson, G.M., and Knudsen, T.

2004   "The Complex Evolution of a Simple Traffic Convention: The Functions and Implications of Habits." *Journal of Economic Behavior and Organization* 54: 19-47.

Huber, J. (Ed.)

1991   *Macro-Micro Linkages in Sociology*. London: Sage.

Kim, J.

2006   "Emergence: Core Ideas and Issues." *Synthese* 151: 547-559.

Kohler, T.A., and Gumerman, J.G (Eds.)

2000   *Dynamics in Human and Primate Societies. Agent-Based Modeling of Social and Spatial Processes*. Santa Fe Institute Studies in the Sciences of Complexity. New York: Oxford University Press.

Laurie, A.J., and Jaggi, N.K.

2003   "Role of Vision in Neighbourhood Racial Segregation: A Variant of the Schelling Segregation Model." *Urban Studies* 40: 2687-2704.

Lomi, A., and Larsen, H.R. (Eds.)

2001   *Dynamics of Organizations. Computational Modeling and Organization Theories*. Cambridge, MA: MIT Press.

Macy, M.

2002   "Social Simulation." In *International Encyclopaedia of the Social and Behavioral Science*, edited by N.J. Smelser and P. Baltes. Oxford: Oxford University Press.

Macy, M., and Willer, R.

2002   "From Factors to Actors: Computational Sociology and Agent-Based Modeling." *Annual Review of Sociology* 28: 143-166.

Manzo, G.

2007   "Le modèle du choix éducatif interdependant. Des mécanismes théoriques aux données empiriques françaises et italiennes." *Archives Européennes de Sociologie* 48: 3-53.

Mark, N.

1998   "Beyond Individual Preferences: Social Differentiation from First Principles." *American Sociological Review* 63: 309-330.

Matthews, R.B., Gilbert, N., Roach, A., Polhill, J.G., and Gotts, N.M.

2007   "Agent-Based Land Use Models: A Review of Application." *Landscape Ecology* 22: 1447-1459.

Mayer, D., and Brown, T.

1998 "The Statistical Mechanics of Voting." *Physical Review Letters* 81: 1718-1721.

Miller, J.H. and Page, S.

2007   *Complex Adaptive Systems. An Introduction to Computational Models of Social Life*. Princeton-Oxford: Princeton University Press.

Moss, S.

2008   "Alternative Approaches to the Empirical Validation of Agent-Based Models." *Journal of Artificial Societies and Social Simulation* 11: http://jasss.soc.surrey.ac.uk/11/1/5.html

Moss, S., and Edmonds, B.

2005   "Sociology and Simulation: Statistical and Qualitative Cross-Validation." *American Journal of Sociology* 110: 1095-1131.

North, D.

2005   *Understanding the Process of Economic Change*. Princeton: Princeton University Press.

Pancs, R., and Vriend, N.J.

2003   *Schelling's Spatial Proximity Model of Segregation Revisited*. University of London, Department of Economics, Working Paper N. 487.

Picker, R.

1997   "Simple Games in a Complex World: A Generative Approach to the Adoption of Norms." *University of Chicago Law Review* 64: 1225-1288.

Prietula, M.J., Carley, K.M., and Gasser, L. (Eds.)

1998   *Simulating Organizations. Computational Models of Institutions and Organizations*. Cambridge, MA: MIT Press.

Rennard, J.-P. (Ed.)

2007   *Nature-Inspired Computing for Economics and Management. II Volumes*. Hershey-London-Melbourne-Singapore: Idea Group Reference.

Ritzer, G.

1990   "Micro-Macro Linkage in Sociological Theory: Applying a Metatheoretical Tool." Pp. 347-370 in *Frontiers of Social Theory. The New Syntheses*, edited by G. Ritzer. New York: Columbia University Press.

Sabater, J., and Sierra, C.

2005   "Review on Computational Trust and Reputation Models." *Artificial Intelligence Review* 24: 33-60.

Saywer, K.G.

2004   "Social Explanation and Computational Simulation." *Philosophical Explorations* 7: 219-231.

2005   *Social Emergence. Societies as Complex Systems*. Cambridge: Cambridge University Press.

Schelling, T.

1971   "Dynamic Models of Segregation." *Journal of Mathematical Sociology* 1: 143-186.

1972   "A Process of Residential Segregation: Neighborhood Tipping." Pp. 157-184 in *Racial Discrimination in Economic Life*, edited by A. Pascal. Lexington, D.C. Heath.

1978   *Micromotives and Macrobehavior*. New York: Norton and Company.

Scott, R.W.

1995   *Institutions and Organizations*. London: Sage.

Sichman, J.S., Conte, R. and Gilbert, N. (Eds.)

1998   *Multi-Agent Systems and Agent-Based Simulation. First International Workshop, MABS '98. Proceedings*. Berlin-Heidelberg: Springer Verlag.

Silberstein, M., and McGeever, J.

1999   "The Search for Ontological Emergence." *The Philosophical Quarterly* 49: 182-200.

Squazzoni, F. and Boero, R.

2002   "Economic Performance, Inter-Firm Relations and Supporting Institutions in Industrial Districts. An Agent-Based Prototype." *Journal of Artificial Societies and Social Simulation* 5: http://jasss.soc.surrey.ac.uk/5/1/1.html.

2004   "Towards an Agent-Based Computational Sociology. Good Reasons to Strengthen Cross-Fertilization between Sociology and Complexity." Pp. 103-133 in *Advances in Sociology Research. Volume II*, edited by L.M. Stoneham. New York: NovaScience Publishers.

Squazzoni, F.

2007   "Does Cognition (Really and Always) Matter? The *Vexata Quaestio* of the Micro-Foundations of Agent-Based Models from a Sociological Viewpoint." Pp. 543-556 in *Interdisciplinary Approaches to the Simulation of Social Phenomena. Proceedings of the Fourth Conference of the European Social Simulation Association*, edited by F. Amblard. Toulouse: IRIT Editions.

Tesfatsion, L., and Judd., K.L. (Eds)

2006   *Handbook of Computational Economics. Volume II: Agent-Based Computational Economics*. Amsterdam: North Holland.

Troitzsch, K.G.

1997   "Social Sciences Simulation. Origins, Prospects, Purposes." Pp. 41-54 in *Simulating Social Phenomena*, edited by R. Conte *et al*. Berlin-Heidelberg: Springer Verlag.

Weisbuch, G., Deffaunt, G., and Amblard, F.

2005   "Persuasion Dynamics." *Physica A* 353: 555-575.

Weisbuch, G., Deffaunt, G., Amblard, F., and Nadal, J.-P.

2002   "Meet, Discuss and Segregate!" *Complexity* 7: 55-63.

Udehn, L.

2001   *Methodological Individualism: Background, History and Meaning*. London-New York: Routledge.

The Micro-Macro Link in Social Simulation

Abstract: This paper aims to look at the problem of the micro-macro link in sociology from the new prospective of social simulation. The adoption of a sociology modelling perspective allows us to sidestep typical domain problems (e.g. individualism vs. holism, action vs. structure, micro vs. macro sociology), for a more pragmatic approach. The first section summarises (due to shortage of space, not exhaustively) the present debate in sociology. The second briefly introduces social simulation as a field of research. The third section presents the analytical constructions that computational social scientists use in dealing with the micro-macro link. The fourth section introduces some clear examples of agent-based models of social outcomes, without entering into technicalities. These examples allow us to pin down some particular mechanisms that can help to map the micro-macro link. The last section summarises our findings and looks forward to questions and challenges that should be explored in the near future.

Flaminio Squazzoni is Assistant Professor of Economic Sociology at the Department of Social Sciences, University of Brescia, Italy, review editor of JASSS-Journal of Artificial Societies and Social Simulation, and Head of GECS-Research Group on Experimental and Computational Sociology (http://www.eco.unibs.it/gecs).