

Agent-based modelling and economic complexity: a diversified perspective

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Received 15 December 2018
Revised 3 March 2019
Accepted 22 March 2019

Abstract

Purpose – The term “agent-based modelling” (ABM) is a buzzword which is widely used in the scientific literature even though it refers to a variety of methodologies implemented in different disciplinary contexts. The numerous works dealing with ABM require a clarification to better understand the lines of thinking paved by this approach in economics. All modelling tasks are a means and a source of knowledge, and this epistemic function can vary depending on the methodology. This paper is to present four major ways (deductive, abductive, metaphorical and phenomenological) of implementing an agent-based framework to describe economic systems. ABM generates numerous debates in economics and opens the room for epistemological questions about the micro-foundations of macroeconomics; before dealing with this issue, the purpose of this paper is to identify the kind of ABM the author can find in economics.

Design/methodology/approach – The profusion of works dealing with ABM requires a clarification to understand better the lines of thinking paved by this approach in economics. This paper offers a conceptual classification outlining the major trends of ABM in economics.

Findings – There are four categories of ABM in economics.

Originality/value – This paper suggests a methodological categorization of ABM works in economics.

Keywords Econophysics, Economic complexity, Agent-based modelling

Paper type General review

1. Introduction[1]

The last three decades have witnessed the emergence of a new scientific term called “complexity science”. Complexity is an unequivocal concept[2] whose definition differs from author to author[3]. Although complexity science seems to be an amalgam of methods, models and metaphors coming from several disciplines, there is a general agreement that a complex system refers to a “many-components system with specific interactions for which locally distinct patterns can be represented in at least one representation of its development” (Zuchowski, 2012, p. 179). However, the notion of complexity is used in so many disciplinary contexts that it favours the development of hybrid areas of knowledge between classical disciplines dealing with complexity. For example, one can mention the emergence of bio-informatics (see Pan *et al.*, 2011) which combines computer sciences and biology for a better understanding of the brain or the development of sociophysics (Galam, 1982, 1986), a branch applying models coming from physics to political and social events. In the same vein, an area combining physics with economics (econophysics) emerged in the 1990s (Jovanovic and Schinckus, 2013a, 2017).

JEL Classifications — B41, C63, C89

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The author declares that there is no conflict of interest regarding the publication of this paper.



Although complexity is a slippery concept, there exists a specialized literature dedicated to “complexity science” in which a lot of different conceptualizations are proposed: hierarchical complexity (Simon, 1962), algorithmic complexity (Chaitin, 1987), stochastic complexity (Rissanen, 1989), compositional complexity (Wimsatt, 1972) dynamic complexity (Day, 1994), computational complexity (Albin and Foley, 1998; Velupillai, 2000), etc. However, whatever the complexity may be, a complex system might roughly be characterized as follows:

By complex system I mean one made up of a large number of parts that interact in a non-simple way. In such systems, the whole is more than the sum of its parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer properties of the whole. (Simon, 1996, p. 4)

The era of complexity in economics generated a lot of studies modelling micro-interactions in which human behaviours are associated with abstract rules generating actions. These studies gave the rise to the emergence of agent-based modelling (ABM) which can be seen as a class of models simulating the actions and interactions of multiple autonomous agents in a complex situation (Bonabeau, 2001). ABM is become a fashionable methodology used in several disciplinary contexts (Epstein, 2006; Silverman, 2018). However, the profusion of works dealing with ABM requires a clarification in order to understand better the lines of thinking paved by this computational approach. ABM generated a lot of debates in economics and it opens the room for epistemological questions about the micro-foundations of macroeconomics (Gallegati and Richiardi, 2009). The scope of this paper only focusses on ABM applied to economic systems by proposing a new methodological categorization for the scattered literature dealing with this issue. This paper aims at clarifying the different uses of ABM to characterize the evolution of economic systems. This methodological categorization will highlight the major epistemological differences between these ways of modelling[4].

After having presented a quick history of the ABM, four ways (deductive, abductive, metaphorical and phenomenological) of implementing an agent-based technique in economics will be analysed. Modelling a complex phenomenon is a means of knowledge implying that the epistemic function of the modelling task can vary to some degree from disciplinary context to another. This paper shows that the different uses of agent-based technique for describing economic systems also refer to different ways of thinking the role of the modelling task.

2. From cellular automata to ABM

ABM is a technique based on a computerized simulation of interactions between a high number of agents whose behaviour has been translated into algorithms. This computational approach finds its origins in cellular automata initially developed by Von Neumann (1951), who worked on self-replication of systems by using a universal Turing machine[5]. Except few studies in the 1960s[6], cellular automata have not really been studied until the seventies when Conway (Gardner, 1970) introduced them in biology and Toffoli (1977) used them to model physical laws.

Cellular automata and related research really grew in the 1980s with the works of Wolfram who found in the Santa Fe Institute[7] a real catalyst for his computerized complexity (he already used this word in the early 1980s). The importance of cellular automata at the SFI has been institutionalized in 1994 when the physicist Jim Crutchfield created the Evolving Cellular Automata Project whose objective was to work on computerized interactions[8]. Because cellular automata can easily be developed through simple rules from which can emerge a very complicated behaviour, they were an ideal starting point to study complexity (Holland, 1986). Although cellular automata are

unquestionably the computational origins of ABM (Epstein, 2006), the methodological perspective of this technique rather dates back to the famous Schelling's (1969) model of racial segregation combined with the adaptive methodology promoted by Brian Arthur and John Holland at the first meeting of the Santa Fe Institute[9] dedicated to economic issues. While the first model is now renowned for explaining that segregationist residential structures can emerge from local behaviour of non-segregationist people[10], Holland (1986) and Arthur (1990a, b) introduced the notion of "complex adaptive system" implicitly based on adaptive individual components (i.e. agents). By component, Holland meant an epistemic entity whose initial configuration (which can be associated with beliefs, preferences or capabilities) allows it to change or adapt its behaviour in an evolving system.

The computational perspective associated with cellular automata promoted by physicists such as Wolfram (1984), Farmer *et al.* (1986) or Kaufmman (1984) combined with a methodological adaptive individualism enhanced by economists (Arthur (1990a, b), and the presence of Arrow at these meetings) and Holland (1986) progressively led to the emergence of what we call now ABM (Waldrop, 1992; Mitchell, 2011; Gallegati, 2018). The 1980s were an appropriate decade for the emergence of complexity studies because computers began to be everywhere (Johnson, 2007). Personal computers were booming and scientists learnt, at that time, how to integrate this new tool in their practices. Computers contributed to science in two ways: on the one hand, they were used as "bookkeeping machines" recording data related to phenomena and, on the other hand, they provided a higher power of computation paving the way to simulation. As Waldrop (1992, p. 63) explained it, "properly programmed, computers could become entire, self-contained worlds, which scientists could explore in ways that vastly enriched their understanding of the real world". Computers can therefore be seen as technical tools enlarging our epistemic access to, on the one hand, the past phenomena (through recording historical data), and, on the other hand, the hypothetical future phenomena (through simulations)[11]. O'Sullivan and Haklay (2000, p. 4) explicitly associated the success of ABM with the increasing computerization of science combined with the academic success of the Santa Fe Institute[12]. The development of computer therefore created the favourable environment for the emergence of complexity paradigm as Waldrop (1992, p. 63) explained it properly, "scientists were beginning to think about more and more complex systems simply because they could think about them".

In the 1990s, one can observe a popularization of computers research-based combined with a gradual computerization of society, offering therefore a large database to investigate. In this context, the ABM has been extended to other disciplinary contexts voting behaviors (Lindgren and Nordahl, 1994), military tactics (Ilachinski, 1997), organizational behaviors (Prietula and Gasser, 1998), epidemics (Epstein and Axtell, 1996), traffic congestion patterns (Nagel and Rasmussen, 1994), etc. ABM has been used in so many fields that it is not possible to number them in this section whose objective was to present a quick historical introduction on ABM. The following part of this paper will focus on the use of this computational method in economics.

3. ABM and economics

Initiated by the Santa Fe Institute in the 1980s, ABM has gradually been developed in the 1990s to become nowadays the most widely used tools to capture the economic complexity. Although that approach allows economists to define some behavioural features, this methodology explicitly associates human behaviours with a set of abstract algorithms supposing to describe the "fundamental behaviour" of agents[13]. In other words, models are formulated in terms of computer programs for which agents' behavioural characteristics are inputs – the outputs are then associated with the macro-level resulting from agents' micro-interactions (Delli Gatti *et al.*, 2018).

Authors involved in modelling of economic micro-interactions try to calibrate the basic behaviour ruling agents' interactions which lead the system to a complex situation (i.e. within macro-properties emerged), as Davis (2013, p. 234) explained it:

In the economy, agent-based modelling generally regards basic self-organizing agents as human individuals, explaining how they respond to changes in their environment in terms of how these individuals change their rules of behaviour in order to satisfy some fitness measure.

The way of defining these rules of behaviour determines the methodological perspective enhanced by modellers. Inspired by Moss (2009), I provide hereafter a methodological classification for works using ABM in economics:

- a deductive approach: the perfectly rational ABM, An abductive approach: the adaptive ABM;
- a metaphorical approach: the bottom-up agent-based econophysics; and
- a phenomenological approach: the top-down agent-based econophysics.

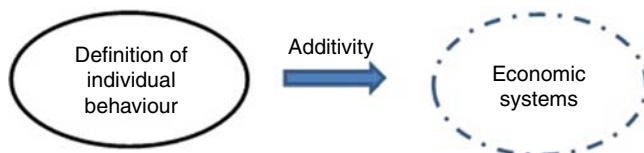
The two first categories are already well documented (Arthur, 1995; Colander, 2000), whereas the two latter are more recent and therefore less investigated in the literature. This section aims at offering a methodological categorization to map the different use of ABM in modelling of economic systems. With this purpose, I will define in more details these four approaches by emphasising their common points but also their major differences; in this context, I will associate the last two approaches with works coming from econophysics that refers to a new area of knowledge and which emerged under the umbrella of complexity. Roughly speaking, econophysics can be seen as the importation of physical concepts/models into economics[14].

3.1 The deductive approach or the perfectly rational ABM

The perfectly rational ABM is the classical methodological individualism used in economics. Interaction rules are defined through a utility function associated with a rational optimization of theoretical constraints, and the system's macroscopic behaviour is deduced from the addition of individuals characteristics. Assumptions are chosen through an intuitive/deductive framework in order to determine a mathematically defined set of interactions which is combined with an assumed perfect additivity of agents in order to estimate the aggregative rule at the macro-level of the system. This classical approach can roughly be summarized as follows.

Figure 1 indicates that a theoretical definition of individual behaviours is postulated without link to the empirical data. The perfect rationality is assumed as a universal principle and the aggregation is used to fit the modelling to concrete situations in which, "the empirical consequences of the theory are deduced from the axioms in the expectation that the deduced will be in agreement with the observed empirical findings" (Bailer-Jones, 2009, p. 84).

Although this way of modelling offers a reliable outcome based on a rational construction, the modelling process itself does not contribute to a potential discovery, it does not teach us



Note: Through a principle of additivity, the macro-system can be deduced from the definition of the initial characterization of agents

Figure 1.
The perfectly rational ABM

more than what we can expect from the definition of the axioms. This deductive framework is well known in economics[15] since it refers to the classical methodology of representative agent according to which the economic macro-result can be described by studying the aggregate economic variables as if differences between actors are negligible or cancel each other on average. Although this way of modelling is still non-standard in economics (rather based on an axiomatic approach), it is quite well used in the field. Economists might not like this approach, but many of them are familiar with it. Although ABM challenged the foundational idea that no interactive agents are described by a fixed utility function, there is an important literature showing that this way of modelling is logically compatible with the mainstream framework (Gallegati and Richiardi, 2009, 2018; Arthur, 2014). Several thematic works can be mentioned here such as the opinion transmission mechanism (Deffuant, 2006; Amblard and Deffuant, 2004), the development of industrial networks and the relationship between suppliers and customers (Brenner, 2001; Gilbert *et al.*, 2001; Epstein, 2006), the addiction of consumer to a brand (Janssen and Jager, 1999), the description of second-hand (cars) markets (Izquierdo *et al.*, 2006), the evolution of financial markets (LeBaron, 2006), etc. [16]. Hamill and Gilbert (2016) and Arthur (2014) offered a very good review of this growing literature. A quick look at the list of the recent winners of the Nobel Memorial Prize in Economic Sciences also gives an indication about the acceptance of ABM in economics. Three people have won this award for their contributions to the development of agent-based economics: Thomas Schelling was the laureate of this prize in 2005 for his contributions to game theory[17]; Elinor Ostrom won this prize in 2009 for her work on the agent-based governance of complex economic systems; and Angus Deaton was awarded in 2015 for his contributions to the micro-foundations (ABM) of consumption, welfare and poverty. The growing importance of ABM can also be observed in finance, in which Meyers (2009) showed how ABM also contributes to the financial mainstream.

3.2 *The abductive approach: the adaptive ABM*

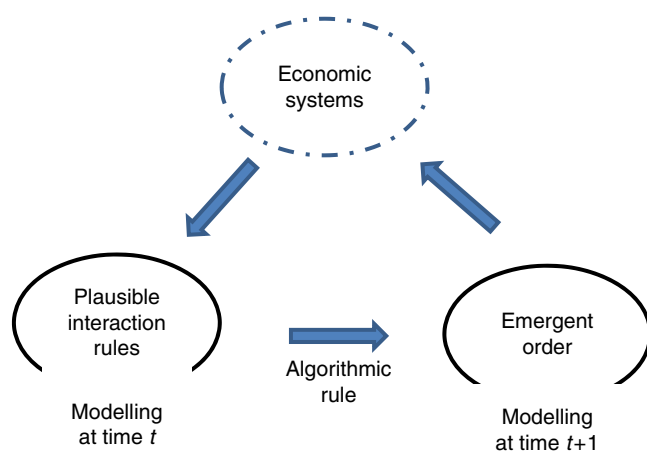
In opposition with this perfectly rational ABM using a principle of additivity to deduce the macro-level, the adaptive ABM rather required a large number of computerised iterations to infer the macro-result[18]. This approach is actually the one associated with the ABM developed at the SFI (Schinckus, 2018a, b). This methodology integrates the heterogeneity and the autonomy of agents considering that “individuals may differ in myriad ways – genetically, culturally, by social networks, by preferences etc.” (Epstein, 2006, p. 6). In other words, no-negligible differences between actors generate a complexity whose analysis requires a computerized simulation. In contrast with the deductive approach, the one based on an adaptive agent does not require the condition of perfect rationality and assumptions are determined through an “intuitive plausibility” (Brock and Durlauf, 2001, p. 35), meaning that micro-interactions are calibrated to meet observed heterogeneity of agents. This ABM is definitely not standard in economics and it still somewhat in the outside of the field (Gallegati, 2018; Delli Gatti *et al.*, 2018).

Adaptive ABM limits the domain of abstract concepts by providing a computerized framework, capturing the relationship between individuals within a specific environment. Hence, this perspective allows to study how agents interact but also how they change their own personal features. The evolving dimension of the process can also progressively transform the agents’ goals. This approach enlarges the way of modelling economic incentives since the algorithmically defined decision functions can integrate some concepts coming from behavioural economics such as overestimation (Lux and Marchesi, 1999, 2000) or conservatism (Chen and Yeh, 2001), etc. Regarding the agents’ autonomy, the adaptive learning abilities defined for agents ensure them particular degree of freedom since they can evolve depending on their plausible interaction rules inspired from economic world (Gallegati and Richiardi, 2009). Once algorithmically defined, these interaction rules are

expected to generate an emergent order far beyond individual capacities or wishes. This kind of modelling could be described by the following schema.

In accordance with a neoclassical perspective, Li Calzi *et al.* (2010) explained that the simpler the algorithmic definition of the rules generating the micro-interactions is, the better the understanding of the macro-results will be [19]. As suggested in Figure 2, modellers try to avoid complicated definitions of micro-interactions which could “obscure the significance of the model, especially if multiple complex rules are acting at once” (Li Calzi *et al.*, 2010, p. 9). These authors justified this perspective as follows: “This appeal to simplicity is nothing more than a restatement of the Occam’s razor principle: why should I use an intricate model if (almost) the same results can be obtained in a cleaner way?” (Li Calzi *et al.*, 2010, p. 2). In other words, the perfectly rational or the adaptive ABM usually describes economic situations in which a macro-behaviour emerged from agents’ behaviour by following simple (and plausible for the adaptive modelling) local rules. The conceptual foundations of these approaches refer to the idea that a decentralized economic system requires the description of agents’ incentives and their interactions structures. In accordance with this view, these agent-based approaches are an incentives-based modelling in which (economic or/and behavioural) motivations must be initially pre-defined. In a sense, the only difference between the perfectly rational and the adaptive ABM refers to the way of inferring the macro-level of the system: while the first is explicitly based on deductive analysis, the latter rather required an algorithmic simulation.

According Gallegati and Rachiardi, (2009), adaptive ABM can be seen as an abductive method because the characterization of individual properties is not enough to deduce the macro-level: “something more is required”. A large number of iterations are needed to infer the best plausible macro-regularity. These computerised iterations generate a specific dynamics in the model which “is designed to imitate the time evolution of a system” (Hartmann, 1996, p. 83). This dynamics has a very important epistemic function since it allows modellers to draw conclusions about the behaviour of the model and therefore about the behaviour of its components (Hughes, 1999). The modelling task has a real epistemic function since, through its evolving computerised iterations, adaptive agent-based models act as a “mediator” (Morgan and Morrison, 1999) between the theoretical understanding and the studied phenomenon. Indeed, the



Notes: The macro-level cannot be deduced from the definition of the characterisation of individual agents. A computerised simulation is necessary to infer the best plausible explanation

Figure 2.
The adaptive ABM

modelling task can be looked on as an interpreted formalism supposing to inform us about a plausible story in our understanding of economic phenomena.

While the model is applied as a mathematical deduction in the perfect ABM, the adaptive perspective of ABM can rather be seen on as a way of exploring and/or extracting the dynamics generating what is studied. Adaptive ABM can be looked on as simulation allowing modellers “to map the model predictions onto empirical level facts in a direct way. Not only are the simulations a way to apply models but they function as a kind of bridge principle from an abstract model with stylised fact to a technological context with concrete facts” (Morgan and Morrison, 1999, p. 30).

Although the economic mainstream (based perfect rationality) is often said to be incompatible with economic complexity (LeBaron, 2006), the perfectly rational ABM can be presented as a complementary approach of the adaptive agent-based framework. Some works combine perfectly rational agents with irrational agents showing that the two frameworks can support and complement each other as Levy (2009, p. 20) explained it:

The Agent Based approach should not and cannot replace the standard analytical economic approach. Rather, these two methodologies support and complement each other: When an analytical model is developed, it should become standard practice to examine the robustness of the model's results with agent based simulations. Similarly, when results emerge from agent based simulations, one should try to understand their origin and their generality, not only by running many simulations, but also by trying to capture the essence of the results in a simplified analytical setting.

The two methodologies presented in this section are the most widely used by economists when they model economic macro-systems based on interactions between micro-agents. Because the perfectly rational agent-based approach and the adaptive perspective are both founded on a micro incentives-based modelling, these two approaches can be looked on as a complementary framework, although the vast majority of works dealing with ABM in economics still refer to the perfectly rational assumption-based modelling.

During the 1990s, the ABM has been increasingly associated with complexity in different disciplinary contexts. In this perspective, scientists mainly coming from physics (econophysics) or biology (econobiology) began to apply their way of implementing agent-based method to economic systems. Econophysics refers to “the extension of physics to the study of problems generally considered as falling within the sphere of economics”[20] (Jovanovic and Schinckus, 2013a, p. 1) implying an importation of physical models into economics. In the same vein, “econobiology” (Rosser, 2010) describes the rise of a biological-based interpretation of economic systems.

The rest of this paper will focus on the two other ways of using ABM to describe economic systems: metaphorical and phenomenological. These two approaches have mainly been developed by scholars coming from other disciplines (biology or physics). The contribution of this methodological categorization is to extend the existing map of ABM methodologies by discussing in more details two very recent perspectives. The two following section will clarify these two physical ways of implementing the ABM in economics.

3.3 *The metaphorical approach: the bottom-up agent-based econophysics*

The majority of papers dealing with ABM in econophysics are related to situations for which micro-interactions are considered as an input and the emerging macro-result is looked on as an output of the process. More precisely, micro-defined agents form an artificial world in which “the ontological and theoretical commitments of agent-based models begin to emerge” (O'Sullivan and Haklay, 2000, p. 6) after a great number of iterations. This computational approach “consists in their displaying complex emergent behaviour, starting from simple atoms deterministically following simple local rule” (Berto and Jacopo, 2012, p. 6). Therefore, methodologically speaking, these studies are in line with ABM used in

economics since a calibration of micro-interactions is required to generate an (unexpected) emerging macro-order. However, some differences exist between these works and agent-based used by economists: in opposition to the latter, the first use non-economic assumptions to calibrate the micro-interactions as explained hereafter.

Aggregate phenomena that exhibit unanticipated properties are not limited to social systems. In physical systems, aggregate phenomena can also appear showing macro-properties distinct from the properties associated with the micro-components. Agents are then considered as interacting particles whose adaptive behaviours create different structures (such as molecules, cells, crystals, etc). This methodological perspective generated a specific literature in economics since some physicists decided to apply it in order to describe the evolution of complex economic systems: Pickhardt and Seibold (2011), for example, explained that income tax evasion dynamics can be modelled through an “agent-based econophysics model” based on the Ising model of ferromagnetism, while Donangelo and Sneppen (2000) or Shinohara and Gunji (2001) approached the emergence of money through studying the dynamics of exchange in a system composed of many interacting and learning agents. In the same vein, some authors used agent-based approach to characterize the emergence of a non-trivial behaviour such as herding behaviour: Eguíluz and Zimmermann (2000), Stauffer and Sornette (1999) or Wang *et al.* (2005), for example, associate the information dissemination process with a percolation model among traders whose interactions randomly connected their demand through clusters. Some econophysicists applied agent-based approach for studying the dynamics of order-driven markets. Bak *et al.* (1997) used a reaction diffusion model in order to describe the orders dynamics. In this model, orders were particles moving along a price line, and whose random collisions were seen as transactions (see also Farmer *et al.* (2005), for the same kind of model). Maslov (2000) tried to make the model developed by Bak *et al.* (1997) more realistic by adding specific features related to the microstructure (organization) of the market. Challet and Stinchcombe (2001) improved the Maslov (2000) model by considering two particles (ask and bid) which can be characterized through three potential states: deposition (limit order), annihilation (market order) and evaporation (cancellation). Slanina (2001) also proposed a new version of the Maslov model in which individual position (order) is not taken into account but rather substituted by a mean-field approximation.

These works can methodologically be characterized by a non-economic agent-based approach since non-economic assumptions are initially made\used for the calibration of the micro-interactions. In this non-economic based approach, a lot of econophysics papers are founded on a what we call the “zero-intelligent agent” (ZI agent) very well summarized by Gode and Sunder (1993, p. 121) when they explained that a ZI agent “it has no intelligence, does not seek or maximize profits, and does not observe, remember, or learn. It seems appropriate to label it as a zero-intelligence trader”.

Actually, ZI agents are conceptually close to atoms since they do not learn, observe or maximize. They are modelled for their ability to interact and they can be considered as physical objects rather than human actors. Another category of works dealing with non-economic based approach use assumptions (and thus algorithmic rules determining micro-interactions) that are defined in terms of “physically plausible events”. In this context, agents and their interactions are defined in terms usually applied to physical systems such as potential states (deposition, cancellation, annihilation, etc.), thermal features (heat release rate, ignition point, etc.) or magnetic dimensions (magnetic permeability, excitation). Whatever they use ZI agents or agents adopting a physically plausible behaviours, econophysicists focus on the physical ability of agent to interact in order to study the kind of order that will emerge from these interactions.

By transferring linguistic terms (concepts\meaning) from physics (source domain) to economics (target domain), this approach refers to a metaphorical way of modelling economic phenomena. In other words, the modelling task is used here as an interpreted (physical)

formalism whose economic meaning is not always easy to understand. That absence of “plausible meaning” in the assumptions is nothing new in philosophy of science since geometrical optics, for example, involve no assumptions about the physical nature of light (Morgan and Morrison, 1999). As Bailer-Jones (2009) explained it, the metaphorical way of modelling initiate transfers whose purpose is often to be a guide to further investigation. Indeed, although an inter-domain transfer is always a delicate issue, it can generate a specific innovation (Bailer-Jones, 2009). Concerning that point, it is worth mentioning that econophysicists obtained different results than those get by economists by applying their specific methodology[21].

From a methodological point of view, physicists involved in this kind of approach implicitly assume a kind of physicalism since they consider that a social reality can be explained in physical terms[22]. That physicalist perspective of economic systems appears to be what Cartwright (1983, p. 133) called an “unprepared description” containing no information that economists could think relevant in terms of existing economic theories. Consequently, there are few links with usual economic knowledge explaining why that kind of agent-based approach is largely ignored by economists. This way of implementing ABM can be described by the following schema.

In a sense, Figure 3 shows that these studies applied the same modelling processing than the ABM used by economists – the only difference refers to an implicit metaphorical equivalence between physical and economic systems. This perspective is often justified by an association of physical plausible understanding of the system under study. For example, some physicists describe the formation of coalitions or the fragmentation of opinions on the market by using the physical phenomenon of spins glasses[23] (Galam, 2008; Pickhardt and Seibold, 2011), while other rather associated herding behaviours with a slow-diffusing process (percolation phenomenon) likely to generate sudden “breakthrough” (Eguiluz and Zimmermann, 2000; Wang *et al.*, 2005).

Despite this category of works widely used in econophysics, it is worth mentioning that this approach is also largely used in literature related to what some authors called “econobiology” (McCauley, 2004; Rosser, 2010; Schinckus, 2018a) that we quickly evoked in the previous section. Although several parts of economics such as evolutionary economics or ecological economics have long been rooted in biology, the emergence of a biological approach on economics rather dates back to Clark (1990), who promoted the development of a bio-economic perspective in order to model the complex economic dynamics.

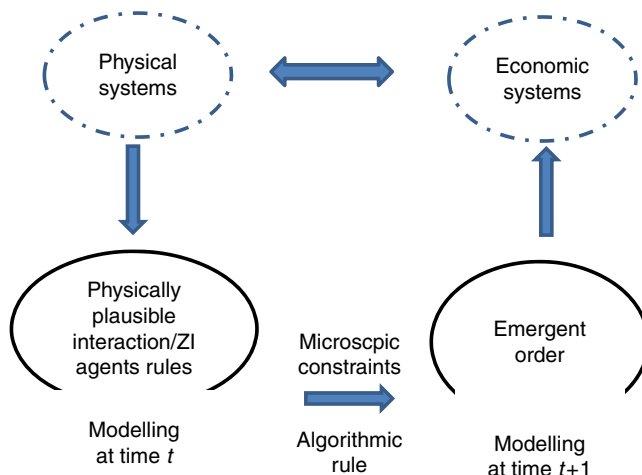


Figure 3.
Bottom-up agent-based econophysics

Though bioeconomics sounds close to econobiology, it is worth mentioning that these two field are quite different[24]. In line with the approach presented in this section, the majority of authors involved in econobiology use a metaphorical bottom-up agent-based technique with the only exception that the assumption calibrating the micro-interactions are defined in terms of “biological plausibility”[25].

The last section of this paper will present a very different way of using ABM since it refers to a top-down methodology. I will present this specific approach through what I call “phenomenological ABM”.

3.4 The phenomenological approach: the top-down agent-based econophysics

This last category of works dealing with ABM of economic systems refers to research whose objective is to reproduce existing statistical data. In opposition to the previous categories of works, authors involved in this area of knowledge usually refer to existing empirical studies which have previously shown the persistence of a specific statistical pattern in economic data. This observation of a macro-statistical pattern is associated with the identification of a discernible and noteworthy phenomenon. Once this phenomenon is identified, the objective is to use its statistical macro-properties as an input for the calibration of micro-interactions which are then supposed to generate the macro-patterns initially observed. In other words, assumptions are empirically determined to fit the data. The real target is not the emergent macro-properties but rather the definition (calibration) of potential micro-interaction likely to generate the initial observed macro-pattern.

In opposition to agent-based economics, individual incentives are not defined as a constraint for the calibration of micro-interactions whose parameterization depends only on the statistical properties of the macro-laws that modellers would like to reproduce. The following diagram can roughly summarize the modelling process of this category of works.

Among works dealing with this technique illustrated in Figure 4, one can mention what econophysicists call the kinetic wealth exchange models whose objective is “to predict the time evolution of the distribution of some main quantity, such as wealth, by studying the corresponding flow process among individuals” (Chakraborti *et al.*, 2011, p. 1026) by using the general theory of transport of energy and finite-time difference stochastic equations in order to generate a predictive power-law distribution related to the evolution of wealth in an economic system. Dragulescu and Yakovenko (2001), Ferrero (2004), Heinsalu *et al.* (2009) or Patriarca *et al.* (2010) provided models describing the transfer of wealth for homogeneous

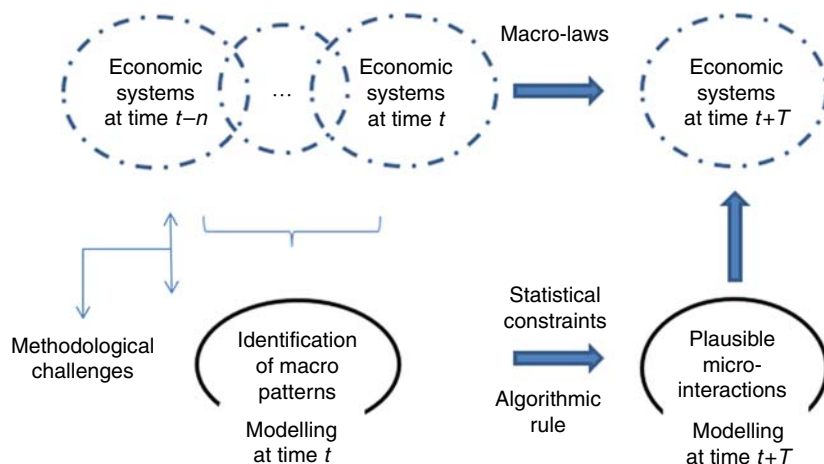


Figure 4. Top-down econophysics

agents (i.e. with the same statistical properties), while Chakraborti and Chakrabarti (2000), Angle (2002), Chatterjee *et al.* (2004), Chakraborti and Parriarca or Chakraborti *et al.* (2015) developed a more complex kinetic wealth exchange model in which agents are diversified (in terms of initial wealth and savings parameter for example). Whereas some studies (Richmond *et al.*, 2013) used Lotka–Volterra equations to describe the wealth distribution, others expressed wealth exchange by using the matrix theory (Gupta, 2006), Markov chains (Scalas *et al.*, 2006) or the Boltzmann equation approach (Slanina, 2004; During *et al.*, 2008). In the same vein, one can also mention Levy *et al.* (1994, 2000), who developed a multi-agent model in which aggregative rule was derived from a particular statistical scheme.

It is worth emphasizing that the modelling task begins with the observation of a macro-pattern (identification of a phenomenon). When econophysicists combine agent-based approach with statistical physics, they target a particular economic system for which a specific macro-law is phenomenologically observed; afterwards, they propose a model based on an algorithmically generated micro behaviour of individual market participants that quantitatively reproduces the pre-identified macro power law. The statistical properties associated with the phenomenological pattern initially identified for an economic system will then be constraining for the calibration of the rules governing interactions between agents, as Feng *et al.* (2012, p. 8388) explained it, “the interaction strength between agents need to be adjusted with agent population size or interaction structure to sustain fat tails in return distributions [i.e. macro-law]”[26]. The objective of this approach is to generate plausible interactions which could reproduce the macro-law observed in real economic systems. According to this phenomenological way of implementing ABM, epistemic role of modelling refers to the identification of the class of events which can be associated with macro-laws (e.g. such power laws) well known by statistical physicists. By combining a micro perspective such as ABM with a strictly macro-description of financial/economic systems, authors involved in this kind of research tried to provide an algorithmic solution to the emergence of statistical invariance. This perspective also echoes to the debates in economics about the micro-foundations of macro-systems (Hayek, 1989; Colander, 2000, 2003).

4. Conclusion

The term “agent-based modelling” is become a buzzword widely used in the scientific literature though it refers to a variety of methodologies that are implemented in different disciplinary contexts. This profusion of works dealing with ABM requires a clarification in order to understand better the epistemic lines of thinking paved by this approach in economics. After a quick historical introduction on the ABM, this paper presents four ways of implementing an agent-based framework to describe economic systems. Modelling task is a source to and a means of knowledge and its epistemic function can vary depending on the methodology used. By presenting the four major agent-based techniques used in economics, this paper clarifies the epistemic role for each of these approaches. Four categories of works have been mentioned in this paper:

- (1) a deductive approach: the perfectly rational ABM;
- (2) an abductive approach: the adaptive ABM;
- (3) a metaphorical approach: the bottom-up agent-based econophysics; and
- (4) a phenomenological approach: the top-down agent-based econophysics.

Although the first two categories are already well documented (Arthur, 1995; Colander, 2000), the two latter are more recent and therefore less investigated in the literature. The objective of this paper is to clarify the situation and offer a methodological map for the different use of ABM in modelling of economic systems. The classical economic approach based on a perfect

rationality has been associated with a deductive way of implementing an agent-based approach in which the modelling task has no real epistemic function since the empirical consequences of the model are rationally deduced by aggregating axioms defining micro-interactions. Afterwards, the adaptive ABM and its abductive reasoning have been presented. The necessity to generate a large number of computerized simulations to infer macro-results gives to the modelling task a real epistemic role where it acts as a mediator between the theoretical formulation of the phenomenon and the reality. The third approach introduced in this paper is the metaphorical ABM in which authors (physicists or biologists) transferred linguistic terms from their discipline (source domain) into economics (target domain). Although this way of modelling often proposes an “unprepared description” in terms of economic meaning, it can also generate a specific innovation (when a theoretical bridge between the source and the target domain is possible). Finally, this paper also presents a more phenomenological way of implementing ABM whose epistemic role seems to focus on the identification of the class of events which can be associated with macro-laws (e.g. such power laws) well known by statistical physicists.

Beyond this methodological categorization of works dealing with the modeling of economic systems, this paper shows the conceptual richness of agent-based based modelling that can be associated with different perspectives/reasoning in scientific research.

Notes

1. This paper discusses different uses of agent-based technique for describing economic systems.
2. As reported by Horgan (1997, p. 305), Llyod identified more than 45 definitions of complexity.
3. From a Kuhnian perspective, this diversity of definition indicates a non-maturity of complexity science which would therefore be seen as a “complexity pre-science” (see Zuchowski, 2012).
4. For a more general perspective on ABM in science, see Beinhocker (2006), Miller (2015) or Silverman (2018).
5. See Chopard and Droz (2005) or Schiff (2011) for further details about the early history of cellular automata.
6. See Moore (1962), Myhill (1963) or Hedlung (1969).
7. Let us remind that the Santa Fe Institute has been founded in 1984 by seven physicists, of which five were based at the Los Alamos National Laboratory (see Waldrop, 1992, Chap. 2). Wolfram attended the first meeting founding the Institute and he has always been an active member of this community.
8. For a good introduction to the themes studied by this research group, see Griffeth and Moore (2003), while Hordwijk (2013) provided a more historical perspective on this group.
9. This adaptive framework based on interacting agents has also been enhanced by Axelrod and Hamilton (1981) and Axelrod (1984), who have been invited to contribute to the Santa Fe Institute in the following year – the call for the use of an adaptive agent-based modelling has been formalized by Holland (1986) and Arthur (1990a, b).
10. Without *a priori* segregationist structure (e.g. such as ghettos), agents generate a global segregation by behaving in line with their local preferences relating their neighbourhood – see Schelling (1969, 1971, 1978).
11. For further details on the impact of computers in economics, see Mirowski (2007).
12. These two elements paved the way to new modelling of evolving complex systems. “The economy as an evolving complex system” was the title of all proceeding volumes related to workshops that Santa Fe Institute organized about economics. See Schinckus (2018a, b) for further information on the topic.

13. In this perspective, “the entire market system is then seen as a network of interrelated individual automata/markomata whose profusion of forms may nonetheless be seen relatively coherent if explained in terms of computational hierarchies” (Davis, 2013, p. 238).
14. See Rosser (2009), Jovanovic and Schinckus (2013a, 2017) or Schinckus (2018a, b) for further details about the emergence of this field.
15. This approach generated a large literature. For further details on the major debates related to this topic, see Dennis (1998).
16. See Cristelli (2014) for a detailed literature review of agent-based modelling applied in economics.
17. The game theory is a mathematical framework that can be tested or implemented through the methodology of agent-based modelling (Bonabeau, 2002).
18. See Epstein (2006), Chen (2012) or Cristelli (2014) for a literature review on this huge literature.
19. That idea seems to be widespread in the specialized literature; see Gilbert (2007), Chen (2012) or Cristelli (2014) for example.
20. See Jovanovic and Schinckus (2013a) for a detailed history of econophysics.
21. See Rosser (2009) or Jovanovic and Schinckus (2013b, 2015) for further details on the innovative potential of these results.
22. Indeed, by using physical concepts to deal with economic/social reality, econophysicists “[physicalists] don’t deny the world might contain many items that, at first sight, don’t seem physical – items of a biological, psychological, moral or social nature. But they insist nevertheless that at the end of the day such items are either physical or supervene on the physical” (Stoljar, 2009, p. 1).
23. “A spin glass is a disordered magnet with frustrated interactions, augmented by stochastic positions of the spins, where conflicting interactions, namely both ferromagnetic and also antiferromagnetic bonds, are randomly distributed” (Zhang, 2012, p. 10). This magnetic phenomenon exhibiting both quenched disorder and frustration, and have often been cited as examples of ‘complex systems (Stein, 2003).
24. Econobiology imports concepts and tools from biology to characterize evolutionary economic systems while bioeconomics refers to the opposite approach consisting of using economic concepts to describe biological systems. For further details, see Schinckus (2018a, b).
25. See Rosser (2010) for a historical presentation of econobiology.
26. It is worth emphasising that econophysicists keep a physical vocabulary in their definition of the interaction rules since they talked about “interaction strength” or “interaction structure”, while economists rather use words “interactions” and “network”.

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Further reading

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