Building ABMs to control the emergence of crisis analyzing agents' behavior

Luca Arciero[1i], Cristina Picillo[1], Sorin Solomon[2], Pietro Terna[3]
[1]*Bank of Italy, Italy;* [2]*Hebrew University of Jerusalem, Israel;* [3]*University of Turin, Italy,*
corresponding author: pietro.terna@unito.it

ABSTRACT

Agent-based models (ABMs) are quite new in the modeling landscape; they emerged on the scene in the 1990s. ABMs have a clear advantage over other approaches: they create the capacity to manage learning processes in agents and discover novelties in their behavior. In addition to bounded rationality assumptions, ABMs share a number of peculiar characteristics: first of all, a bottom-up perspective is assumed where the properties of macro-dynamics are emergent properties of micro-dynamics involving individuals as heterogeneous agents who live in complex systems that evolve through time.
To apply this framework to financial crisis analysis, a simplified implementation of the SWARM protocol (www.swarm.org), based on Python, is introduced. The result is the Swarm-Like Agent Protocol in Python (SLAPP).
Using SLAPP, we can focus on natural phenomena and social behavior. In our case, we focus on the banking system, recreating the interactions of a community of financial institutions that act in the payment system and in the interbank market for short-term liquidity.

INTRODUCTION: LITERATURE REVIEW

... there is no general principle that prevents the creation of an economic theory based on other hypotheses than that of rationality (K. J. Arrow, 1987)

The *raison d'être* of Agent-based models (ABMs) lies in a vision of the world that is completely different from the conventional view of rational choice theory, which prevails in economics.
Beginning with Adam Smith's idea of the "invisible hand", the (minor) history of economic science may be represented in a stylized fashion as a progressive refinement of the rational agent hypothesis, which first materialized in profit (utility)-maximizing agents and, later, in the Lucas and Sargent rational expectation theory.
In the game theoretical strand of economic science, the rational agent paradigm translates into infinitely forward- and backward-looking agents that are usually endowed with common knowledge about their opponent's rational behavior.
Although infinitely rational, strategies elaborated by these agents may be proven as less successful than simpler strategies based on heuristics and shortcuts, as witnessed by the famous Axelrod tournament reported in Schellenberg (1996). Axelrod invited game theorists and behavioral economists to play an iterated prisoner's dilemma by submitting computer programs translating the strategies that they thought a player should follow during the game. A number of scholars joined the tournament: some of them presented complex software replicating forward- and backward-looking agents, and others submitted simple programs mimicking agents' behaviors with simpler rules, heuristics and shortcuts. The simplest of these programs was the one named "Tit for Tat," built by Anatol Rapoport, a famous psychologist. The

artificial agent embedded in the Rapoport "Tit for Tat" program acted on a minimal decision tree (represented in four instructions), which led the agent to cooperate at the first iteration and then to match the opponents' strategy: cooperate if the other cooperates, and defect if the opponent defects. Against every forecast, the Rapoport program won the tournament. Surprisingly, "Tit for Tat" emerged the winner in a second tournament in which the artificial agents embedded in the competing programs had been built to challenge "Tit for Tat" on the basis of complex decision trees. It was not the surprise effect that enabled "Tit for Tat" to overcome its opponents in the first tournament; Rapoport's artificial agent emerged as the most effective program, even though other artificial agents had been aware of its behavior.

The Rapoport "Tit for Tat" software history unavoidably recalls the concept of "bounded rationality," originally introduced by Nobel Laureate H. Simon in the 1950s as a "rational choice under computational constraints," whose specific ingredients are i) the limited, sometimes fuzzy, information regarding possible alternatives to a specific problem and the related consequences at the agents' disposal; ii) the limited ability of the agents to elaborate the available pieces of information; and iii) the limited amount of time agents can spend deciding. Given these constraints, agents tend to adopt "satisficing" rather than optimizing behavior by relying on rules of thumb, heuristics and shortcuts to deliberately save resources (Simon, 1955).

The plausibility of the bounded rationality paradigm has been confirmed by a great deal of additional experimental evidence rooted in the seminal works of Daniel Kahneman, Amos Tversky, and their collaborators (who laid the foundation of an enormous body of literature on the topic). Among their main contributions (such as Tversky and Kahneman, 1992) was the discovery of the framing effects governing the decision processes of the agents whose choices do not depend on the contents of the choice but rather on the way that the decision problem is framed, i.e., the way the alternatives are presented.

Against this background, the need emerges for an approach that combines both complexity and simple heuristic rules in a balanced way.

A first alternative is experimental economics—whose initial applications date back to the 1950s, and which has been experiencing an ever-growing acceptance among academics—where real individuals are assigned cash incentives to maximize their expected profits to replicate the incentives operating in the real world and to draw inferences on market function.

To give an example of how experimental economics works, we choose, from among the thousands of experiments carried out thus far, an experiment developed by Cipriani and Guarino (2005), who set up an experiment based on the Glosten and Milgrom (1985) asymmetric information model to investigate the extent to which noise trading can be ascribed to trader irrationality in a laboratory financial market.

In the Cipriani and Guarino experiment, subjects receive private information on the value of an asset and trade it in sequence with a market maker. By observing the trader strategies and being aware of the model parameters, the authors estimate a structural model of sequential trading, finding that the noise in their experiment is due to the irrational use of private information accounts for 35 percent of decisions.

Experimental economics benefits from the presence of real subjects, who are given real cash incentives, in a model in which researchers can collect observational data that are not surrounded by confounding factors hiding the real world parameters. Experimental economics is not a panacea (Davis & Holt, 1993). Major drawbacks include the difficulty of replicating real incentives (people may exhibit different degrees of risk aversion in response to different amounts at stake) and a sort of selection bias (people cannot be forced to join an experiment). Other drawbacks include difficulties in designing and studying complex experiments close to real-world situations and iterating an experiment several times with the same players to study learning mechanisms.

Against this backdrop, a possible solution is moving from real, human individuals to fictitious agents. These agents can be generated by software and can be assigned complex tasks, behavioral rules and proper incentives. The artificial behavior of these agents can be examined for a considerable amount of time.

In this vein, ABMs represent a suitable methodology for analyzing highly decentralized, highly parallel complex systems. Using an ABM with each agent (i.e., with each individual element of the system) is represented through a vector of attributes and a set of simple micro-level rules and heuristics governing the agent's behavior. Furthermore, the experiment design is under the complete control of the modeler, who decides how the virtual agents are defined and initialized.

A common feature of ABMs is the assumption of Simon's concept of bounded rationality, which can be subdivided into in a number of alternative options, as agents may vary greatly, exhibiting different degrees of sophistication. Reactive agents are the simplest agents because they are built and programmed to merely react to external stimuli, are unable to elaborate strategies, and usually have no memory, thus resembling the behavior of Pavlov's dog more than the behavior of a human. An early example of reactive agents can be found in the Gode and Sunder's "zero intelligent" agents[ii] (1993), who post bids or offers in a double-auction model, comparing market prices with their reservation prices, without making any assumptions about the behaviors of the other agents. Even the models based on reactive agents have proved effective in reproducing real dynamics. The drawback of this approach is that the agents are too naive to adapt to unforeseen situations.

Deliberative agents lie opposite of reactive agents. Deliberative agents behave according to their knowledge about the external world and to their past experiences, and they elaborate strategies to achieve given targets[iii]. These agents' ability to cope with uncertainty is not a free lunch: deliberative agents are likely to devote a (sometimes) unnecessary amount of time to elaborating and evaluating a set of alternative strategies, even in simple situations.

Hybrid agents involve a combination of the two approaches: they can respond to routine changes within the environment without elaborating complex, time-consuming strategies, but they maintain the ability to elaborate new strategies and plans when they are asked to cope with unprecedented situations.

Another attractive property of ABMs is the possibility of allowing them to modify their behavior through learning. "Reinforcement learning" techniques are widely used in ABM models, as they ensure that actions that provide profitable outcomes are "reinforced" and assigned a greater probability of being taken in the future. Other possible ways are the use of genetic algorithms or of learning of classifier systems (which are also commonly embedded in several ABMs to allow them to optimize and adapt their behavior).

Even though there is room for improving learning mechanisms in ABMs, agent-based simulation is a flexible tool for modeling system dynamics in the presence of learning mechanisms because, once created, agents may be forced to live for a certain period in a world where time and space are explicitly managed to evolve agents' behavior using parallel techniques.

In addition to bounded rationality assumptions, ABMs share a number of peculiar characteristics. First, a bottom-up perspective is assumed where the properties of macro-dynamics are emergent properties[iv]—and not in equilibrium outcome, as in the neoclassical models—of micro-dynamics involving individual, heterogeneous agents living in complex systems that evolve through time. A further common feature of ABMs is the interaction among economic agents, which takes place in a direct and inherently non-linear fashion, as agents elaborate their decision on the basis of past choices made on their own and by other agents in the population.[v]

ABM models have become more and more effective since their initial applications [such as von Neumann's (1966) self-replicating machine and Conway's (Gardner, 1970) game of life], allowing the emergence of credible macro-level dynamics even when individuals are assigned simple rules and are assumed to be homogeneous.

An early and well-known example of the application of the ABM paradigm in the field of economics is the Santa Fe Artificial Stock Market, which was developed in the late 1990s. The Santa Fe Artificial Stock Market is a simple model reproducing trading dynamics with agents embedded with simple rules mapping the states of the world into buy or sell decisions. Despite its simplicity, this artificial market can replicate several features that resemble the statistical properties of real financial data: excess kurtosis of returns, little linear autocorrelation and persistent volatility (LeBaron et al., 1999). Applications of ABM to economic modeling span a broad range of research topics: from market design (Tesfatsion, 2011), technology diffusion (Gilbert et al., 2001) and the labor market (Neugart, 2008) to banking regulations (Westerhoff, 2008), central banks (Rapaport et al., 2009) and systemic risk. An example: Geanakoplos et al. (2012) created an ABM that reproduces the process leading to the formation and burst of the US real estate bubble, which played a crucial role in triggering the mortgage crisis. Running counterfactual analyses, the authors find that leverage (i.e., loan to value ratio), rather than low interest rates, was the main driver of the crisis.

As discussed in the case of experimental economics, we cannot refrain from highlighting the major limits and challenges that ABMs still face despite their growing popularity. Echoing Leo Tolstoy in Anna Karenina, "Happy families are all alike; every unhappy family is unhappy in its own way"[vi], models are correct in only one way but may be wrong in several ways. In fact, when removing the hypothesis of rational choice, behavioral functions may be represented by an infinite number of plausible heuristics and shortcuts, inducing a sense of arbitrariness in the model (Rubinstein, 1998). Recently, there has been a great deal of work addressing the issue of ABM validation, proposing a number of different approaches to ABMs' empirical validation, among which the history-friendly approach, the indirect calibration approach and the Werker-Brenner (2004) approach may be considered the most influential (Windrum et al. 2007).

The history-friendly approach consists of calibrating the parameters and defining the behavioral rules embedded in the model to mimic specific actual features with a view to closely replicating the empirically observable history of a particular phenomenon. However, the indirect calibration approach and the Werker-Brenner approach avoid imposing ex-ante a set of restrictions on parameters; instead, they rely on empirical evidence to delimit specific sub-regions in the potential parameter space, where the model is able to give rise to actual statistical regularities or stylized facts.

Despite the efforts of ABM researchers, no approach has been recognized as a standard, universally agreed upon method for validating ABMs. Therefore, model validation still represents the greatest challenge that ABMs must face to be fully accepted by scholars.

Finally, to conclude this brief discussion of agent-based modeling, it is worth mentioning that ABMs still lack a unique, agreed upon protocol for building models. To shed light on this issue, in the next paragraph, we present the making of a large ABM based on the SLAPP protocol originally introduced by Terna (2010). (See `http://eco83.econ.unito.it/terna/slapp/`.)

FROM THE SLAPP PROTOCOL TO A CONCRETE APPLICATION

What is the Swarm protocol, and should we care about it?

SLAPP, the Swarm-Like Protocol in Python, was used to build our simulation model. It comes from Swarm (Minar et al., 1996; Swarm can be accessed via `www.swarm.org`.) The Swarm project started at the Santa Fe Institute (first release: 1994) and represents a milestone in simulation.

Swarm has been highly successful; its protocol is the basis of several recently released tools, such as Repast, Ascape, NetLogo and StatLogo, and JAS. SLAPP is one of Swarm's most simplified reproductions, as it is written in Python (`www.python.org`). The original Swarm implementation was written in Objective C, a powerful language (which is the object-oriented merge of C and SmallTalk), which had a limited diffusion in the mid-1990s. Objective C is now quite popular; it is the base of the Mac OS X operating system. A second version of Swarm, with its main core always written in Objective C, but usable in Java, was released in the late 1990s. Swarm's popularity was limited by the beginning of the 2000s due to the lack of maintenance of its complex structure in the face of the new releases of the operating systems (also in the Linux case). JAS (`sourceforge.net/projects/jaslibrary/`) is similar to Swarm but is pure Java. SLAPP is similar to Swarm, with significant addenda, such as the original AESOP (Agents and Emergencies for Simulating Organizations in Python) layer, implemented in Python to take advantage of the simplicity of the language and its advanced internal structure, which has native powerful features.

According to Minar et al. (1996):

> Swarm is a multi-agent software platform for the simulation of complex adaptive systems. In the Swarm system the basic unit of simulation is the *swarm*, a collection of agents executing a schedule of actions. Swarm supports hierarchical modeling approaches whereby agents can be composed of swarms of other agents in nested structures. Swarm provides object oriented libraries of reusable components for building models and analyzing, displaying, and controlling experiments on those

models.

To summarize the paper of Minar et al., (i) Swarm defines a structure for simulations, a framework within which models are built; (ii) Swarm's core commitment is creating a discrete-event simulation of multiple agents using an object-oriented representation; (iii) to these basic choices, Swarm adds the concept of the *swarm*, a collection of agents with a schedule of activity; and (iv) the simulation of discrete interactions between agents stands in contrast to continuous system simulation, where simulated phenomena are quantities in a system of coupled equations. These are the key ideas of the ABM technique.[vii]
We see the first step of the protocol in Fig. 1, with a collection of bugs that need to be managed in a discrete-event simulation environment, following a schedule of actions. The *modelSwarm* contains the space where the bugs behave, the bugs and a clock.

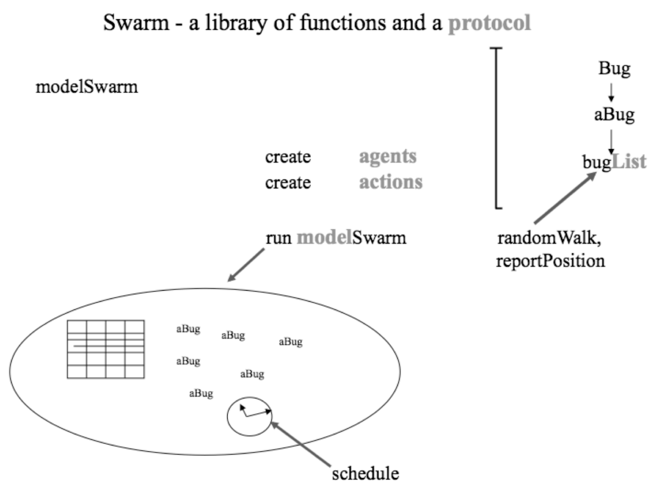

Figure 1 - The basis of the Swarm protocol, with (i) the steps of the creation of the agents and of the schedule, (ii) the model and (iii) the collection of the agent to which we send the orders from the schedule.

The sequence that the protocol suggests is as follows: create the agents (or bugs, in our case) and then create the actions to be executed by the agents. In our case, we have a *class* or *set* named *Bug* (the initial capital letter is not mandatory but represents a useful convention), and from that class, we generate the required number of instances (named *aBug*) of the class. We place all of the generated instances into a collection, here named *bugList*. For us, it is irrelevant that the formal name of each instance is always the same because the *list* will contain the information that is necessary to address each instance individually. After the creation of the agents, we prepare the actions to be taken (*randomWalk* and *reportPosition*) when the clock of the model, following the schedule, requires each action to be executed by each agent or by a specific agent. Using the collections, the code works with any number of agents because actions are addressed to the collection, which send the request to all of the collection's components. If a specific agent must act instead, the order is sent directly to that agent.
We have also to observe the behavior of our model. In Fig. 2, we add a higher level of analysis by introducing an observer (*observerSwarm*), which contains the model and has objects (the model, the tools to observe it) and an independent schedule managed by a clock different from that of the model. It is normally not necessary to observe the model outcomes with the same granularity of the events occurring within the model itself.

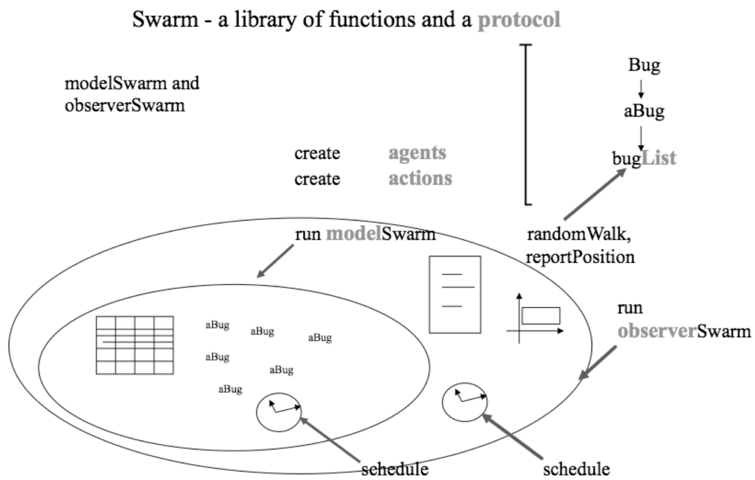

Figure 2 - We add a new layer, the observer, containing the model and the tools used to view it.

In Fig. 3, we add the probes as tools that allow us to look directly into the agents to inspect their data while the model is running. This tool is useful both for searching for errors in the code and for analytically evaluating the behavior of the components of the model. SLAPP does not currently have this capability (which is, instead, a pillar of the NetLogo agent-based platform).

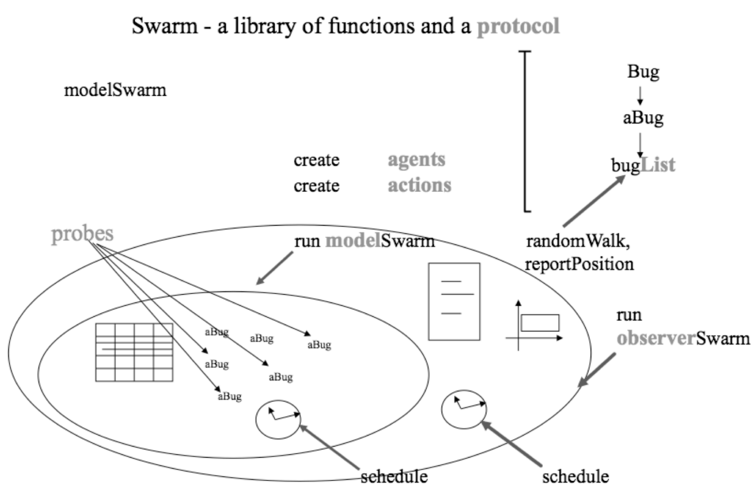

Figure 3 - Via the probes, we can directly inspect the data of each agent.

A concrete application to the P&3M (Payments and Money Market Model)

Using an ABM and, in our case, SLAPP as preferred tool, we can focus both on natural phenomena and economic or social behaviors. For example, in the banking system case, we can recreate the interaction of a community of financial institutions that interact via both a payment system and an interbank market for short-term liquidity. Here, we show the importance of ABM for understanding potential systemic risk and the contagion effects arising from liquidity shortages.
Modeling such a problem with an ABM is particularly attractive because the financial crisis has shown that securities and funding markets are potentially affected by sudden, (unexpected) deep modifications in agents' actions, which may be fruitfully analyzed through ABMs equipped with learning machines.

Quoting Tirole (2011) on market liquidity breakdowns (pp. 298–299), we can rely on authoritative advocacy to support our statement:

> Market liquidity presumes that there are buyers (of assets, of securities) on the other side. As the recent crisis has demonstrated, this need not be the case. Commentators have accordingly mentioned the possibility of a "buyers' strike" a surprising concept for economists (...).

Before we enter into the details of the model, it is worth describing the institutional features of the environment under investigation. According to a consolidated definition (Bank for International Settlement, 2001), a payment system consists of a set of instruments, banking procedures and, typically, interbank funds transfer systems that ensure the circulation of money. In turn, interbank funds transfer systems (IFTS) are arrangements among banks and a settlement agent, typically central banks, that hold settlement accounts on behalf of participants and manage the settlement process of debiting and crediting the participants' account according to the payment instructions they submit to the system.

Currently, the majority of IFTS, which is hereafter referred to as a payment system, operates in a Real-Time Gross Settlement (RTGS) fashion, meaning that each payment submitted to the system is settled immediately in central bank money (cash), provided that sufficient liquidity is held in the participants' accounts.

The flows of incoming and outgoing payments create surplus or deficit of liquidity at the participant level, both on an intraday and a daily basis. On the intraday basis, liquidity deficits may prevent banks from executing payments with potential delay costs because their customers or other banks may perceive delaying banks as unreliable. Under certain stressful situations, banks delaying "critical" payments may bear enormous costs, as they may be perceived as illiquid, prompting other banks in the system to question their viability. Such questioning carries potential implications for systemic risk.

Banks commonly have a desired end-of-day level of cash in their accounts. This target comes from the reserve requirement regime imposed by central banks on commercial banks' monetary policy operations. This minimum reserve regime requires banks to hold in their central bank accounts a certain amount of cash in proportion to their short-term liabilities over a certain maintenance period. Thus, banks set intermediate daily desired end-of-day targets, with the growth of the average balance over the maintenance period in mind.

To manage their payment flows, banks may borrow and lend cash that they need not only on an intraday and daily basis in the interbank market (hereafter called the money market), usually on a bilateral, over-the-counter basis, but also on a multilateral basis, through screen-based electronic markets, as is the case of the e-MID Italian electronic exchanges for uncollateralized exchanges.

Our ABM model focuses on the liquidity management problem of commercial banks, which face a payment obligation that must be settled in an interbank fund transfer system under the intraday, end-of-day and multi-day constraints. This liquidity management problem can be solved by relying on the money markets.

The case presented closely resembles the Italian framework because Italian banks execute part of their trading in the money market through a screen-based multilateral market and settle their payment obligations through an RTGS system (the same RTGS system, TARGET2, is used in all of the countries in the Euro zone). From the model, some conclusions can be drawn about the design of mechanisms that aim to contain financial risk and to avoid contagion and cascading failures.

We introduce here a hybrid framework (see above). The agent-based model operates not only with the treasurers of the banks as agents but also with the interbank payment system as an agent within the model, moving payments around, with delays and failures determined by the treasurers. Payments create shortages and abundances of liquidity in banks by generating asks and bids in the money market, via a double auction system, as in a regular stock market. In this way, the model links both the behavior of the treasurers and the time distribution of the payments with the short-term movements of the interest rate.

Using SLAPP and ABM, we shift the focus on the concrete aspects of an actual banking system by recreating the interaction of two institutions (a payment system and a market for short-term liquidity) to investigate interest rate dynamics in the presence of delays in interbank movements. The delay problem is a crucial one because delays in payments can generate liquidity shortages that, in the presence of unexpected negative operational or financial shocks, can produce huge domino effects (Arciero et al., 2009). In this perspective, agent-based simulation is a magnifying glass for understanding reality.

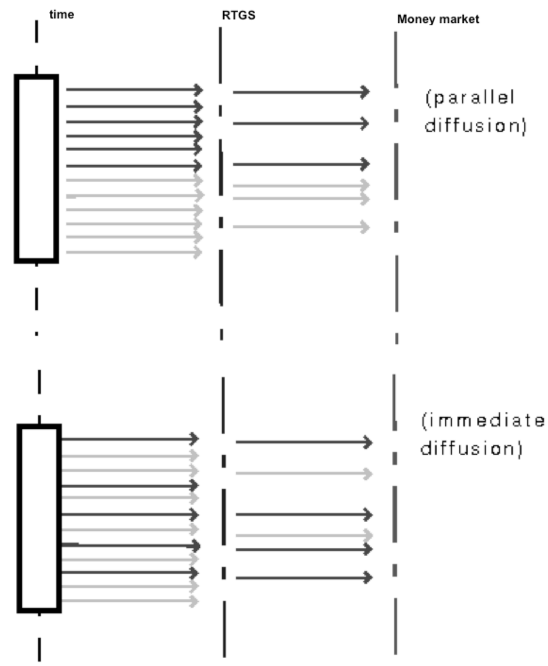

Figure 4 - A UML (Universal Modeling Language) representation of the actions taken by agents over time. Black arrow: a treasurer making a payment and bidding a price to obtain the money via the money market. Grey arrow: a treasure receiving a payment and asking a price to employ the money via the money market.

We have two parallel and highly connected institutions: a RTGS, or Real Time Gross Settlement system, as described in Arciero and Impenna (2001); and an e-MID-like money market (electronic Market of Interbank Deposit, which is a standard double continuous auction market, with the special characteristic that asks and bids are identified by the name of the actor; see `www.e-mid.it/?lang=uk`). To avoid any misunderstanding, the asking agent requires a price, the interest rate, to lend money. On the contrary, the bidding agent offers a price for borrowing money. Considering the flow of interbank payments settled via the first institution, we simulate delays in payments and examine the emergent interest rate dynamics in the money market. In this type of market, the interest rate is the price. The behavior in this market is complicated by a few microstructures that will be investigated.

In Fig. 4, we have a modified representation of the standard sequence diagram of the UML (Unified Modeling Language, `www.uml.org`) formalism that introduces time as the main actor in the sequence. Time, as the actor, is important because our model, and the related agents' behavior, is event driven. What are the events in our case? The events are the payments effectively recorded in a given time interval that come from actual interbank money movements on a gross basis, i.e., without any clearing effects, as required by central banks all around the world (Angelini, 1998).

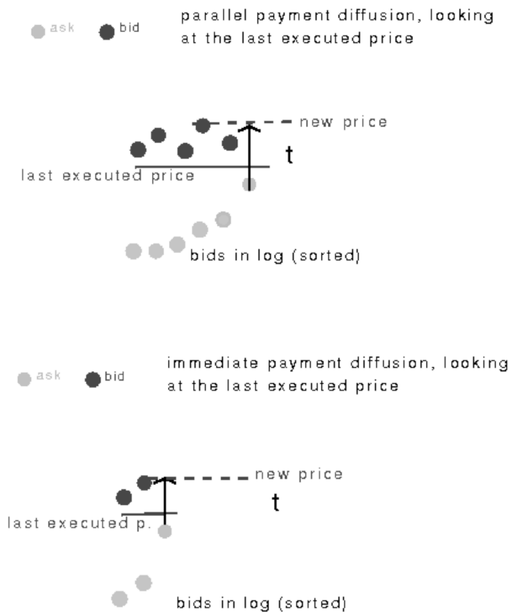

Figure 5 - (a).

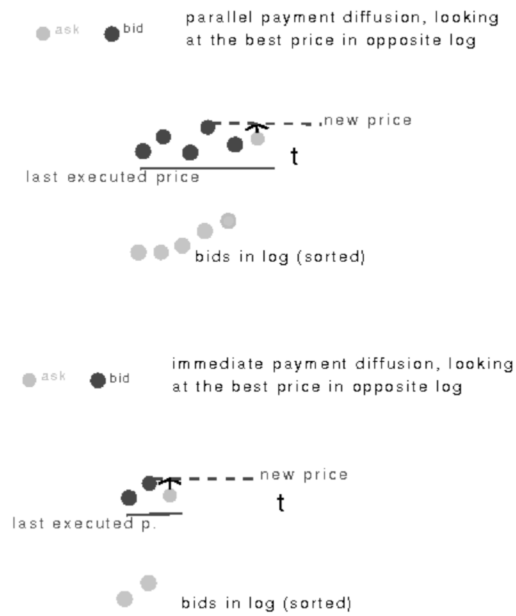

Figure 6 - (b).

(a) Viewing the last executed price, both in a parallel and immediate diffusion scheme
(b) Viewing the best proposal in the opposite market log, both in a parallel and immediate diffusion scheme.

Events come from an archive of actual data and follow a time schedule that is sent to our simulated environment (we used artificial data to prepare the program; the code was applied to actual data only when running internally to the Bank of Italy). The treasurers of the banks, who receive payments or have to make payments via the RTGS system, bid prices with given probabilities to buy liquidity in the money market or ask prices to sell liquidity in the same market. Bid and ask probabilities can differ. The mechanism of bidding or asking on a probabilistic basis (if and only if a payment must be executed or has been received, as in Fig. 4) is also related to the liquidity balance of the specific bank. As a consequence, the bid and ask mechanism is indirectly related to the whole set of financial movements of a given time period.

The different sequences of events (with their parallel or immediate diffusion, as in Fig. 4) generate different lists of proposals into the double-auction money market that we analyze. Proposals are reported in logs: the log of the bid proposals, according to decreasing prices (first listed: bid with the highest price); and the log of the ask proposals, according to increasing prices (first listed: ask with the lowest price). “Parallel” means that we are considering an actual situation in which all of the treasurers make the same kind of choices at the same time. “Immediate” means that we have a situation in which the treasurers are acting step by step, in a mixed way, both bidding and asking simultaneously.

In Fig. 5, we discuss how a new price is proposed to the market when we consider the last executed price as a reference point and place a price below it to obtain an easily matched ask position. In this case, both the cases of parallel proposals and immediate diffusion are expected to produce close results. In Fig. 6, a new price is proposed to the market by considering the best proposal in the opposite log as a reference point and placing a price below it to obtain again, in a different way, an easily matched ask position. The cases of parallel proposals and immediate diffusion are now expected to produce different effects. As can be verified here, market microstructures are highly important in an ABM.

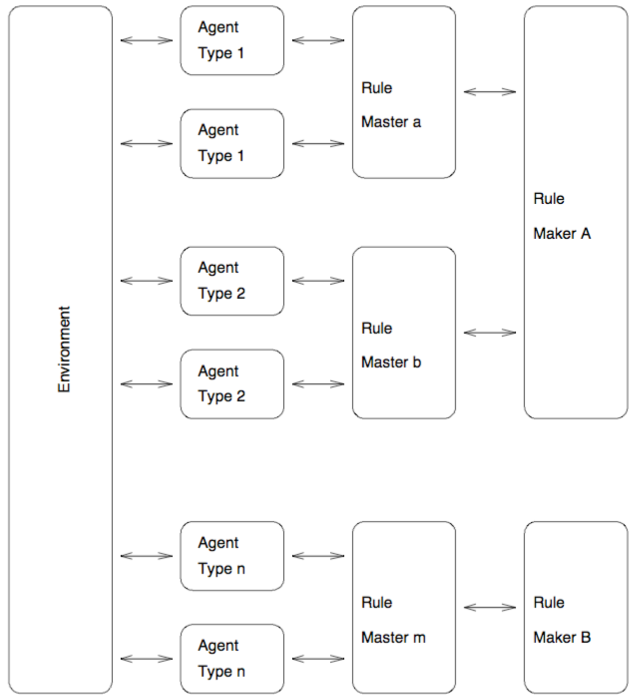

Figure 7 - The Environment-Rules-Agents (ERA) scheme (Gilbert and Terna, 2000). See `http://web.econ.unito.it/terna/ct-era/ct-era.html` *for more details.*

We see that, following the Swarm protocol, the *Model* is responsible for creating the agents as a class (*Banks*), each single agent (*aBank*) and the list of all agents (*BankList*). The protocol is also responsible for shaping the agents' actions. The time runs on an internal schedule of events based on a simulated clock. This clock triggers, at specific moments, the actions of the entire class of agents or of single agents. However, another schedule exists: that of the external *Observer*, who monitors the development of the actions and interactions within the *Model* and whose time does not necessarily elapse at the same speed as that of the *Model*. The *Observer* can stop the model execution. For example, the *Observer* can consider the interactions among the agents in a very specific instant of the simulation or run statistics on the simulated world up to that moment.

The *Observer* is also responsible for shaping the agents' characteristics (e.g., number, interconnectedness, level of required reserves, initial account balances) as well as determining the economic variables that condition the agents' behavior (monetary policy determinants, such as the interest rate and the level of the monetary aggregates).

Behavioral rules within P&3M

Different layers of rules do coexist in the model. Following the SLAPP scheme and the ERA convention in Fig. 7, we can introduce how rules are represented within the model. The main value of the Environment-Rules-Agents (ERA) scheme, introduced in Gilbert and Terna (2000), is that it keeps both the environment, which models the context by means of rules and general data, and the agents, with their private data, at different conceptual levels.

With the aim of simplifying the code design, external objects determine agent behavior. *Rule Masters*, for instance, can be interpreted as abstract representations of the cognition of the agent. Production systems (sets of fixed rules), classifier systems, neural networks and genetic algorithms are all candidates for the implementation of *Rule Masters*.

We may also need to employ meta-rules, i.e., rules used to modify rules (for example, the training side of a neural network). The Rule Master objects are therefore linked to *Rule Maker* objects, whose role is to modify the rules mastering agent behavior, for example, by means of a simulated learning process.

P&3M general principles are embedded within the framework from which all of the possible behavioral rules of our banks stem. Examples of *Rule Maker* contents are compliance with the minimum reserve requirement, profit maximization, opportunity cost minimization, and payment timeliness versus delay in a repeated game perspective. From *Rule Makers*, any number of specific rules can be derived. The rules can affect all of the agents (profit maximization) or only a specific subset of agents (greedier banks versus more prudent banks). Additionally, the same rule can have different gradations, particularly regarding trade-offs (e.g., avoiding opportunity costs at any price versus a different intensity of tolerance, accepting opportunity costs against the costs of delaying payments or being forced to raise money on the interbank market to fulfill obligations).

How the model works

The starting principles of P&3M (Payments and Money Market Model) are in Arciero and Picillo (2012); a detailed presentation of the model is at `http://eco83.econ.unito.it/terna/P&3M/P&3M.html;` finally, the code can be obtained by contacting the corresponding author.

The model is fed either with exogenous real world data or artificially generated data. The model's parameters can be finely tuned either through an initial panel or input files. Banks are the agents: in each tick, all banks are asked to act in a random order, relying on prescheduled incoming and outgoing payments (actual data, when used, stem from the Italian RTGS system). The actions are based on empirical patterns inferred from the behavior of market participants on e-MID, the Italian electronic multilateral interbank money market platform, and on anecdotal evidence yielded during contacts with banks' treasurers. The schedule of the model is characterized by time breaks that represent the end of the day. In fact, the simulation embraces a *multiday* interval, mimicking the reserve requirement maintenance period. The single payment includes a progressive number, a start time and an end time, the sending and receiving bank, and the amount. When we use artificial data, a delay can be added to the starting time, assuming that the treasurer has the opportunity to evaluate whether to pay immediately or with a delay. The delay is defined as a random draw from a uniform distribution between zero and a plausible upper limit. The same effect could be introduced into the real world data by applying an *undelay*, assuming that the original due time of a payment is not always the one at which the transaction is really settled and may be a moment in time before the effective timestamp. Additionally, the *undelay* is a random draw from a uniform distribution.

The P&3M model manages situations in which a payment is due but the agent does not have enough liquidity on its account to settle it immediately. The payment will be bounced, delayed and resubmitted for settlement in the subsequent tick of the internal schedule, whereas the needed liquidity will be either supposed to flow in if the expected end-of-day balance exceeds the due amount or *purchased* on the interbank money market. To have a market clearing end-of-day, payments that cannot be fulfilled are dropped and settled via correspondent banking.

The parallelism of the different actions (i) determines the flow of payments and the smoothness of the functioning of the payment system, as in Fig. 8; (ii) populates the money market book; and (iii) influences the interest rate dynamic. These aspects are captured by output reports generated by the P&3M model, both in terms of aggregate statistics that allow capturing the outcome of the complex interaction of the agents and their rules as well as in terms of micro-level indicators.

We show now an interesting case of the dynamics emerging from this simulation environment. This case occurs when the diffusion of the payment into the RTGS system is parallel and the operators consider the last executed price in the money market. The run reported in Fig. 8 shows a non-trivial behavior of the interest rate. The dynamic is magnified here due to the dimension chosen for micro-movement in bids and asks. In these five days, we see a large movement of this time series as a consequence of significant delays in interbank payments. The simulation runs step by step, but we account for breaks in time to reproduce the end of each day (i.e., cleaning all the positions, etc.).

In Fig. 8, we have the following: the interest price dynamic (upper line), stock of due payments (intermediate line), and flow of the received payments (lower line) in case of relevant delay in payments (with a uniform random distribution between 0 and 90% of the available time until the time break). Time breaks (day changing) occur at 20, 40, … ticks.

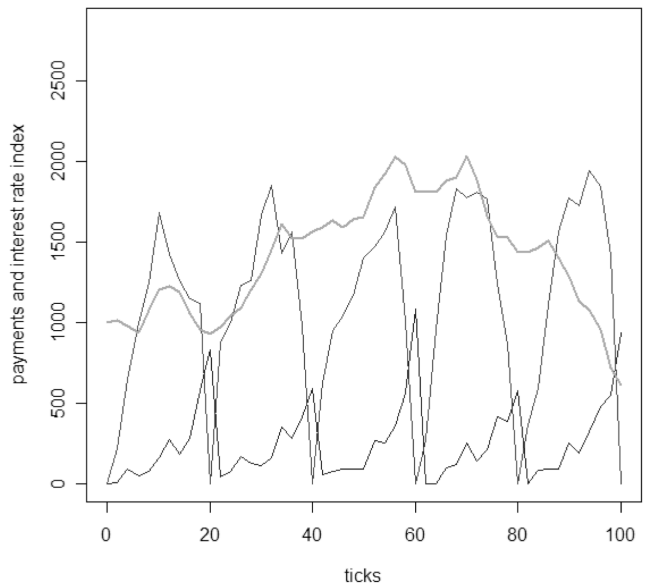

Figure 8 - The interest price dynamic (upper line), stock of due payments (intermediate line), and flow of received payments (lower line).

By elaborating the interest rate series with the standard AR (autoregressive) and MA (moving average) techniques and directly connecting SLAPP to R (`http://www.r-project.org`), we find a typical AR(1) model in the graphs of the second row in Fig. 9.

For the time being, the general principles have been designed as fixed and have been imposed by an external *god*. Future work will be focused on the introduction of a system of reinforced learning, where the agents will update the superior governing principles that can be emended and updated based on the experience yielded by the interaction with other agents within the environment.

Further research related to the technical functioning of the P&3M model will entail differentiating between "bland" and "tasty" agents. Bland agents are the simple, unspecific and basic agents whose behavioral rules operate in the background of the simulation. These actions are carved in the basic code implementing the SLAPP protocol. Tasty agents, the ones on which a researcher will focus, are subjects with specific predetermined skills and discretionary powers (acting capabilities). The rules governing the agents' actions operate in the foreground of the simulations in the sense that they are not fixed in the underlying code but rather are explicitly managed via scripts that can be *steered* by a researcher in an explicit way. These scripts will allow for the application of rules on different sets of agents with different numbers of elements. For example, the researchers will have the opportunity to decide whether an increased risk perception affects a specific kind of bank in any desired moment of the simulated days. From a technical point of view, this decision can be performed by creating an ad-hoc agent for each role in which a tasty agent is desired.

In this way, we have an artificial, but close to real, artifact that reproduces the interbank payment system and serves as an actual tool for policy analysis. For instance, the artifact can experiment with modifications in rules and control the daily behavior of the market, simulating the market while it evolves. Imagine having the ability to explore a set of possible realistic continuations of the payments and money market access in the middle of each day to fine-tune the interventions of the central bank in order to face potential liquidity issues. This simulation would be a non-trivial application of the model. Unfortunately, such an application is quite far from our present capabilities of the model.

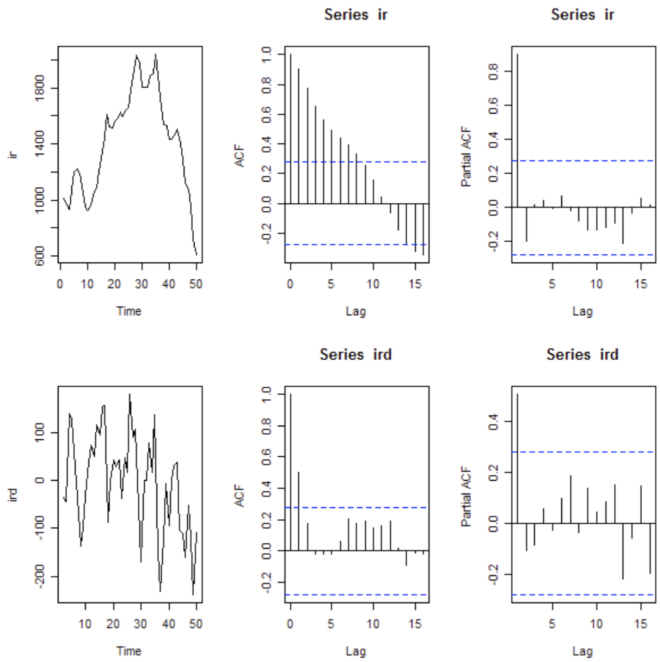

Figure 9 - The autocorrelation analysis of the interest rate data of Figure 8 (with the presence of delays in interbank payments). First row: raw data; lagged correlations among data; and the same, but as partial correlations. Second row: data first differences with lag 1; their lagged correlations; and their lagged partial correlations.

A QUITE LONG CONCLUSION: INTEGRATING DIFFERENT TECHNIQUES

When managing the effects of emerging novelties in agent behavior, we must consider a research path that takes us from abstraction to realism. This means coping with complexity.

The standard economic approach compresses the complexity of reality into the mathematical structure of models based on ex-ante hypotheses arising from classic paradigms, such as rationality in behavior, thus ignoring interaction and sociality among real-world agents. The use of these models for individual and collective choices determines the ineffectiveness of corrective actions of policies. The first step in a pro-social direction is to bring the equations of the models to the level of individual agents (possibly with some degree of heterogeneity closer both to realism and to social dimension. Particularly in the presence of heterogeneity, doing so is a step ahead of pure numerical simulation but still too closely tied to the standard paradigm. If agents stylize their equations to operate (calculate) in a system with institutions (for example, a trading system), the model takes another step toward realism and usefulness. However, we believe that this type of achievement is insufficient.

Quoting Trichet (2010), the former president of the European Central Bank:

> When the crisis came, the serious limitations of existing economic and financial models immediately became apparent. Arbitrage broke down in many market segments, as markets froze and market participants were gripped by panic. Macro models failed to predict the crisis and seemed incapable of explaining what was happening to the economy in a convincing manner. As a policy-maker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt abandoned by conventional tools.

The consequence was that policy makers found very limited help and guidance in standard economic models. The policy makers used judgment and historical analysis, with an increasing number of risks.

Thus, it is necessary to take a few steps ahead in new directions to offer new tools that can be used with the traditional ones.
Quoting Trichet:

> (…) The atomistic, optimizing agents underlying existing models do not capture behavior during a crisis period. We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. We need to entertain alternative motivations for economic choices. Behavioral economics draws on psychology to explain decisions made in crisis circumstances. Agent-based modeling dispenses with the optimization assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention.

We are now very close to the ABM perspective suggested above, mainly from the point of view of capturing unexpected actions and behavior. A large project awaits us: the construction of models that can compare in a parallel way to (i) the standard setting of the purely mathematical model; (ii) equations that reproduce behavior in a decentralized way and with heterogeneity; and (iii) agent interaction through institutions and rules vs. (iv) the use of models that are completely based on agents, both with simple behavioral skills or arbitrarily complex ones. These skills are related to the structures of relationships, mutual influence, information, and learning capabilities.
From our perspective, it is crucial to introduce a capability for developing forms of *intelligent behavior* that allow agents to plan actions randomly or trivially in a starting phase, but in successive steps, to verify the effects of their behavior via ABMs as well as to use tools, such as artificial neural networks, to memorize the positive or negative effects of their choices. An alternative approach with genetic programming is another possibility.
While the elements listed above constitute a powerful and promising starting point for constructing a system of thinking and a corresponding system of acting, their integration into a solid, coherent basis is still a difficult and lengthy challenge. The unexpected and threatening recent collapse of the financial system has been an extreme incentive to base the steering of financial and economic systems on more scientific, systematic and commonly accepted procedures. To achieve this, we must fulfill a series of difficult syntheses.

1. *Integrate multi-agent methods into traditional macroeconomic thinking*. Recently, agent-based methods (also with statistical mechanics, phase transitions, percolation, multi-scale, localization, spatially extended stochastic processes) have been used by a number of groups, but the emphasis has been on the interactions between simple agents. The integration into those models of bi-directional feedback between agents' actions and macro-economic phenomena, entities and expectations has yet to be fully expressed and understood. In fact, the lack of top-down mechanisms in the initially proposed models was one reason why economists treated them with justified reservation. While including all of the relevant factors of the economic world in our models is an enormous and perhaps intimidating multidisciplinary task, the formulation of agents is, in the long term, uniquely suited for expressing and incorporating such a collection of eclectic elements and for representing faithfully the ultimately human nature that underlies economic systems.
2. *Integrate the theoretical models with the data*. The neoclassical synthesis and the game theory methods used in economics are mathematically rigorous and allow one to express precisely a variety of ideas, methods and mechanisms. In fact, their conceptual crispness often impedes their contact with empirical reality, which has accidents, the subjectivity of human behavior and the related serendipity, and the extreme irregularity of (endogenous and exogenous) events. Maybe it is useful to remember that the statistical methods of statistical physics were designed to deal with elements that are full of *impurities* and to study the systemic effects of such *impurities*.
3. The difficulty of applying precise mathematical theorems to imperfect, concrete reality has also complicated the *application of academic results to policy and decision making*. The results of research

have been cast in a language and format that are not always familiar and or immediately relevant to practitioners. In the opposite direction, the flow of information from practitioners to academics has frequently been limited by a lack of detailed data on the financial and economic systems. Even today, data are scattered and not entirely publicly available, typically due to confidential constrain. However, recent events have incited the practitioners (private practitioners and regulators) to seek more contact with academics. From the academic side, the formulation of ideas into the language of individual agents and their specific actions is much more understandable and translatable to concrete decisions and policy[viii]. Researchers' access to the details of individual financial and economic transactions and the tight feedback between modeling and real action is a promising and sine qua non condition for upgrading the degree of control one has over financial and economic phenomena.

This line of work can allow us to empirically verify the relevant feedback interactions between macro (institutional, emergent) and micro (individual agents) entities, which in turn can guide us in formulating models that theoretically represent empirical reality.

REFERENCES

Angelini P. (1998), An analysis of competitive externalities in gross settlement systems. *Journal of Banking & Finance*, 22 (1), pp. 1-18, http://www.sciencedirect.com/science/article/pii/S0378426697000435, verified September 2013.

Arciero, L., Biancotti, C., D'Aurizio, L., & Impenna, C. (2009), Exploring agent-based methods for the analysis of payment systems: a crisis model for StarLogo TNG. *Journal of Artificial Societies and Social Simulation*. http://jasss.soc.surrey.ac.uk/12/1/2.html. Verified September 201ter
3.

Arciero, L. and Impenna, C. (2001), Time pattern of payments in the Italian RTGS system: the effect of institutional financial variable. Technical report, Banca d'Italia. http://www.bancaditalia.it/sispaga/sms/sistemi/pag ingrosso/sistemi sistemi bi 5.pdf. Verified September 2013.

Arciero, L. and Picillo, C. (2012), Analysing the Large Value Payment Systems: need for an agent-based models complex approach. In: B. Alexandrova-Kabadjova, S. Martinez-Jaramillo, A. L. Garcia-Almanza, E. Tsang (Eds.), *Simulation in Computational Finance and Economics: Tools and Emerging Applications*. Hershey, PA: IGI Global. .

Arrow, K. J. (1987). Rationality of self and others in an economic system. In: R. M. Hogarth & M. W. Reder (Eds.), *Rational Choice* (pp. 201–217). The University of Chicago Press.

Bank for International Settlement (2003). *Glossary of terms used in payments and settlement system,*. Report prepared by the Committee on Payment and Settlement Systems of the Central Banks of the Group of Ten Countries Basel, March 2003

Becker, G. S. (1962). Irrational behaviour and economic theory. *Journal of Political Economy* 70, 1–13.

Cipriani, M. & Guarino, A. (2005). Herd Behavior in a Laboratory Financial Market. *American Economic Review*, 95(5), 1427–1443.

Davis, D. D. & Holt, C.A. (1993). *Experimental economics*. Princeton University Press.

Gardner, M. (1970). The fantastic combinations of John Conway's new solitaire game life. *Scientific American*, 223. 120–123.

Geanakoplos J., Axtell R., Doyne Farmer J., Howitt P., Conlee B., Goldstein J., Hendrey M., Palmer N.M. & Yang C. (2012). Getting at Systemic Risk via an Agent-Based Model of the Housing Market, *American Economic Review*, vol. 102(3), pages 53-58, May.

Gilbert, N., Pyka, A. and Ahrweiler, P. (2001). Innovation Networks – A Simulation Approach. *Journal of Artificial Societies and Social Simulation*, 4(3), 1-13.

Gilbert, N. and Terna, P. (2000), How to build and use agent-based models in social science. *Mind & Society*, 1(1), pp. 57–72.

Glosten, L. R. & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*,14(1), 71–100.

Gode, D. K., Sunder, S., (2004). Double auction dynamics: structural effects of non-binding price controls. *Journal of Economic Dynamics and Control* 28 (9), 1707–1731.

Ladley, D. (2012). Zero Intelligence in Economics and Finance, *The Knowledge Engineering Review - Special Issue on Agent Based Computational Economics*, 27(2), 273-286.

LeBaron, B., Arthur, W. B. & Palmer, R. (1999). Time series properties of an artificial stock market, *Journal of Economic Dynamics and Control* **23**, 1487–1516.

Minar N., Burkhart R., Langton C., and Askenazi M. (1996), The Swarm Simulation System: A Toolkit for Building Multi-Agent Simulations. *SFI Working Paper*, 06 (42),.
URL `http://www.santafe.edu/media/workingpapers/96-06-042.pdf`. Verified September 2013.

Neugart, M. (2008). Labor market policy evaluation with ACE. *Journal of Economic Behavior and Organization,* 67, 418-430.

Rao, A. & Georgeff, M. (1991). *Modeling Rational Agents within a BDI-Architecture*. In: Proceedings of the 2nd International Conference on Principles of Knowledge Representation and Reasoning. Morgan Kaufmann publishers Inc.

Rapaport, O., D. Levi-Faur and D. Miodownik (2009). The Puzzle of the Diffusion of Central-Bank Independence Reforms: Insights from an Agent-Based Simulation, *Policy Studies Journal*, 37: 695 - 716.

Rubinstein, A. (1998). *Modeling Bounded Rationality*. Cambridge, MA: The MIT Press.

Schellenberg, J. A. (1996). *Conflict Resolution: Theory, Research and Practice*. State University of New York Press.

Simon, H. (1955). A Behavioral Model of Rational Choice. *Quarterly Journal of Economics*, 69(1), 99–188.

Terna, P. (2010), A new agent-based tool to build artificial worlds. In: M. Faggini & C. P. Vinci (Eds.), *Decision Theory and Choices: a Complexity Approach* (pp. 177–191). Heidelberg: Springer.

Tesfatsion L. (2001). Structure, behavior, and market power in an evolutionary labor market with adaptive search, *Journal of Economic Dynamics and Control*, 25(3): 419-457.

Tirole, J. (2011). Illiquidity and all its friends. *Journal of Economic Literature*, 49(2), 287-Ð325.

Trichet, J. C. (2010). *Opening address at the ECB Central Banking Conference*, Frankfurt, 18 Nov. `http://www.ecb.int/press/key/date/2010/html/sp101118.en.html`. Verified September 2013.

Tversky, A. & Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty*, 5(4), 297–323.

Von Neumann, J. (1966), *The Theory of Self-reproducing Automata*. University of Illinois Press.

Werker, C. & Brenner, T. (2004), *Empirical Calibration of Simulation Models*. Papers on Economics and Evolution 2004-10. Max Planck Institute of Economics, Evolutionary Economics Group.

Westerhoff, F. (2008). The use of agent based financial market models to test for the effectiveness of regulatory policies. *Zeitschrift für Nationalökonomie und Statistik (Journal of Economics and Statistics)* 228, 195-227.

Windrum, P., Fagiolo, G., Moneta, A. (2007). Empirical validation of agent-based models: Alternatives and prospects. textitJournal of Artificial Societies and Social Simulation, 10(2). 8–22. `http://jasss.soc.surrey.ac.uk/10/2/8.html`. Verified September 2013.

KEY TERMS & DEFINITIONS

SLAPP, the Swarm-Like Agent-Based Protocol, at `http://eco83.econ.unito.it/terna/slapp`, is the general shell we use here to develop the models. Verified September 2013.

P&3M, `http://eco83.econ.unito.it/terna/P&3M/P&3M.html`, the Payments and Money Market Model, is the specific agent-based simulation program introduced here. Verified September 2013.

RTGS, both as a payment system and as a source of data, is the Real Time Gross Settlement System; see `http://www.bancaditalia.it/sispaga/sms/sistemi/pag_ingrosso/sistemi_sistemi_bi_5.pdf`. Verified September 2013.

eMID, the Electronic Market for Interchange Deposits, is the money market; see details and explanations at `http://www.e-mid.it/?lang=uk`. Verified September 2013.

ADDITIONAL READING SECTION

About agent-based models

Allan, R. J. (2010). *Survey of agent based modelling and simulation tools*. Technical report, Science & Technology Facilities Council.

Axelrod, R. (1997). Advancing the Art of Simulation in the Social Sciences. In R. Conte, R. Hegselmann, and P. Terna, editors, *Simulating Social Phenomena*, volume 456 of Lecture Notes in Economics and Mathematical Systems, pages 21-40. Springer, Berlin.

Axelrod, R. and Tesfatsion, L. (2005). A guide for newcomers to agent-based modeling in the social sciences. In K. L. Judd and L. Tesfatsion, editors, *Handbook of Computational Economics*, volume 2, pages 1647-1658. North-Holland. URL http://www.econ.iastate.edu/tesfatsi/GuidetoABM.pdf.

Axtell, R. (2000). *Why Agents? On the Varied Motivations for Agent Computing in the Social Sciences*. In Proceedings of the Workshop on Agent Simulation: Applications, Models and Tools. Argonne National Laboratory, IL. URL http://www.brookings.edu/~/media/Files/rc/reports/2000/11technology axtell/agents.pdf.

Boero, R., Bravo, G., Castellani, M. and Squazzoni, F. (2010). Why bother with what others tell you? an experimental data-driven agent-based model. *Journal of Artificial Societies and Social Simulation*, 13(3):6. ISSN 1460-7425. URL http://jasss.soc.surrey.ac.uk/13/3/6.html.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *PNAS*, 99(Suppl. 3):7280-7287.

Borrill, P. L. and Tesfatsion, L. (2010). *Agent-based modeling: The right mathematics for the social sciences?*, Iowa State University, Department of Economics. URL http://econpapers.repec.org/RePEc:isu:genres:31674.

Cioffi-Revilla, C. (2010). Computational social science. *Computational Statistics*, 2(3):259-271.

Cristelli, M., Pietronero, L. and Zaccaria, A. (2011). *Critical Overview of Agent-Based Models for Economics*. ArXiv e-prints. URL http://arxiv.org/abs/1101.1847.

Fagiolo, G. and Roventini, A. (2012). Macroeconomic policy in dsge and agent-based models. *EconomiX*. URL http://www2.econ.iastate.edu/tesfatsi/MacroPolicyDSGEACE.FagioloRoventini2012.pdf.

Gaffeo, E., Gallegati, M. and Gostoli, U. (2012). *An agent-based "proof of principle" for walrasian macroeconomic theory*. Technical report, Cognitive and Experimental Economics Laboratory, Department of Economics, University of Trento, Italia, 2012. URL http://www-ceel.economia.unitn.it/papers/papero12 02.pdf.

Gallegati, M. and Kirman, A. (2012). Reconstructing economics: Agent based models and complexity. *Complexity Economics*, 1:5-31.

Isaac, A. G. (2008). Simulating evolutionary games: a python-based introduction. *Journal of Artificial Societies and Social Simulation*, 11(3):8. http://jasss.soc.surrey.ac.uk/11/3/8.html.

Isaac, A. G. (2011). The ABM template models: A reformulation with reference implementations. Journal of Artificial Societies and Social Simulation, 14(2):5. http://jasss.soc.surrey.ac.uk/14/2/5.html.

M. A. Janssen and E. Ostrom. Empirically based, agent-based models. Ecology and Society, 11(2):37, 2006.
URL http://groups.forestry.oregonstate.edu/fpf/system/files/Janssen%20and%20Ostrom%202006.pdf.

Kirman, A. (2010). Learning in Agent-Based Models. *Eastern Economic Journal*, Vol. 37, Issue 1, pp. 20-27.

LeBaron B. (1998). Agent based computational finance: Suggested readings and early research. *Journal of Economic Dynamics and Control*, 24:679-702.

LeBaron, B. and Tesfatsion, L. (2008). Modeling macroeconomies as open-ended dynamic systems of interacting agents. The American Economic Review, 98(2):246-250.

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H. and Schwarz, N. (2013). Describing human decisions in agent-based models - odd+d, an extension of the odd protocol. *Environmental Modelling & Software*, 48:37-48. http://www.sciencedirect.com/science/article/pii/S1364815213001394.

North, M. and Macal, C. (2009). Agent-based modelling and systems dynamics model reproduction. International Journal of Simulation and Process Modelling, 5(3):256-271.

Sakellariou, I., Kefalas, P. and Stamatopoulou, I. (2008). Enhancing NetLogo to simulate BDI communicating agents. *Artificial Intelligence: Theories, Models and Applications*, pp. 263-275. http://users.uom.gr/~iliass/projects/NetLogo/Papers/Extending_NetLogo_SETN08_SVerlag_Camera_ready.pdf.

P. Siebers, C. Macal, J. Garnett, D. Buxton, and M. Pidd. Discrete-event simulation is dead, long live agent-based simulation! Journal of Simulation, 4(3):204,Äì210, 2010.

N. Smith. Development as Division of Labor: Adam Smith Meets Agent-Based Simulation. http://papers.ssrn.com/sol3/papers.cfm?abstract id=2173846.

Vriend, N. J. (1999). *Was Hayek an ace?* http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.140.5808.

Windrum, P., Fagiolo, G. and Moneta, A. (2007). Empirical validation of agent-based models: Alternatives and prospects. *Journal of Artificial Societies and Social Simulation*, 10(2):8. http://jasss.soc.surrey.ac.uk/10/2/8.html.

About payment systems

Angelini, P. (2002). Are Banks Risk-Averse? Timing of the Operations in the Interbank Market, *Journal of Money, Credit and Banking*, *32*(3), 54-73.

Arciero, L. (2012). Evaluating the impact of shock in the supply of overnight unsecured money market funds on the TARGET2-Banca d'Italia functioning: a simulation approach, *Rivista Bancaria - Minerva Bancaria, Istituto di Cultura Bancaria Francesco Parrillo*, issue 2-3, June.

Ashcraft, A.B., & Darrell, D.(2007). Systemic Illiquidity in the Federal Funds Market, *American Economic Review*, 97(2), 221-225.

Bank for International Settlement (1997). *Real-time Gross Settlement Systems.* Report prepared by the Committee on Payment and Settlement Systems of the Central Banks of the Group of Ten Countries, Bank for International Settlements, Basle.

Diehl, M. (2013). The Use of Simulations as an Analytical Tool for Payment Systems. In B. Alexandrova-Kabadjova, S. Martinez-Jaramillo, A. Garcia-Almanza, & E. Tsang (Eds.), *Simulation in Computational Finance and Economics: Tools and Emerging Applications* (pp. 29-45). Hershey, PA: Business Science Reference. doi:10.4018/978-1-4666-2011-7.ch002.

Heijmans, R., and Heuver, R. (2013). Preparing Simulations in Large Value Payment Systems using Historical Data. In B. Alexandrova-Kabadjova, S. Martinez-Jaramillo, A. Garcia-Almanza, & E. Tsang (Eds.), *Simulation in Computational Finance and Economics: Tools and Emerging Applications* (pp. 46-68). Hershey, PA: Business Science Reference. doi:10.4018/978-1-4666-2011-7.ch00311111101.

Galbiati, M., & Soramäki, K. (2011). An agent-based model of payment systems. *Journal of Economic Dynamics and Control, 35*(6). 859-875.

Giansante, S. (2009). *Agent-based Economic (ACE) Modelling of Payments Media: Emergence of Monetary Exchange, Banking, Large Value Payment and Settlement Systems*, University of Essex, Centre for Computational Finance and Economic Agents (CCFEA), Ph.D Thesis.

Laine, T., Korpinen, K., & Hellqvist, M. (2013). Simulation Approaches to Risk, Efficiency, and Liquidity Usage in Payment Systems. In B. Alexandrova-Kabadjova, S. Martinez-Jaramillo, A. Garcia-Almanza, & E. Tsang (Eds.), *Simulation in Computational Finance and Economics: Tools and Emerging Applications* (pp. 69-83). Hershey, PA: Business Science Reference. doi:10.4018/978-1-4666-2011-7.ch004.

Klee, E. (2010). Operational Outages and Aggregate Uncertainty in the Federal Funds Market, *Journal of Banking and Finance*, 34(10), 2386-2402.

Kokkola T. (2010). *The Payment System: Payments, Securities and Derivatives, and the Role of the Eurosystem.* European Central Bank.

Laine, T., Korpinen, K., & Hellqvist, M. (2013). Simulation Approaches to Risk, Efficiency, and Liquidity Usage in Payment Systems. In B. Alexandrova-Kabadjova, S. Martinez-Jaramillo, A. Garcia-Almanza, & E. Tsang (Eds.), *Simulation in Computational Finance and Economics: Tools and Emerging Applications* (pp. 69-83). Hershey, PA: Business Science Reference. doi:10.4018/978-1-4666-2011-7.ch004.

Leinonen, H. and Soramäki, K. (2003). Simulating interbank payment and securities settlement mechanisms with the BoF-PSS2 simulator. *Bank of Finland Discussion Papers, No 23/2003*, Suomen Pankki.

Manning, M., Nier, E. & Schanz, J. (2009). *The Economics of Large-Value Payments and Settlement: Theory and Policy Issues for Central Banks*, Oxford University Press, Oxford.

Markose, S., Alentorn, A., Millard, S., & Yang, J., (2011). *Designing large value payment systems: An agent-based approach* (University of Essex Economics Department Discussion Paper No. 700). Colchester: University of Essex.

McAndrews, J., & Trundle, J. M. (2001). New payment system designs: causes and consequences. *Bank of England Financial Stability Review, 11(2001).* 127-136.

Sheppard, D. (1996). Payment Systems. *Handbooks in Central Banking, No 8*, Centre for Central Banking Studies, Bank of England, London, 1996.

Spaanderman, J. J. (2012). A central bank perspective on liquidity management, *Journal of Financial Market Infrastructures*, Volume 1/Number 2, Winter 2012/13 (65–78).

Summers, B.J. (1994). *The Payment System: Design, Management, and Supervision*. International

Monetary Fund.

---

[i] The opinions expressed are those of the authors and do not necessarily reflect the views or the opinions of the Banca d'Italia.
[ii] The Zero Intelligent approach precedes the advent of the ABM, which was originally introduced by the Nobel Laureate G. Becker in 1962. For an extensive review of the Zero Intelligence approach for the analysis of financial market, see Ladley (2004).
[iii] The BDI model (Belief, Desire, Intention) introduced by Rao and Geogeff (1991) is perhaps the most popular paradigm for deliberative agents. BDI agents interpret the macro changes occurring within the environment, record the information acquired and act proactively.
[iv] See also Chapter 1.
[v] See also Chapter 16.
[vi] Translated by Constance Black Garnett (1862-1946) in 1917.
[vii] See also Chapter 9.
[viii] See also Chapters 7 and 8.