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Artificial Financial Markets: Historical and Interdisciplinary Perspective

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Abstract: *This paper aims to present the architecture of an artificial stock market that considers the microstructure of existing markets and understanding the complex patterns and phenomena that are observed in economic systems. In agent-based financial market models, prices can be endogenously formed by the system itself as the result of interaction of market participants. We identify and describe the tasks and choices that different traders face based on their role in the market by tracing orders. We review the literature on these models and analyze their strengths, weaknesses, opportunities, and threats with special focus on traders. We conclude with seven recommendations to help guide the development of artificial markets as a venue for technological innovation research.*
Keywords: *Complex systems, Evolutionary Approach, Artificial Markets, SWOT analysis.*

I. Introduction

Financial markets are complex constructs that are not always easy to understand. It is even not possible to explain the function of financial markets on basis of theoretical analysis, since theory normally assumes fully rational agents. Notably, rational investors use unbiased expectations in forming and selecting mean-variance efficient portfolios. Violations of this assumption are quite common and stem from behavioral characteristics. It gives rise to bounded rationality and heterogeneity in modeling investors' decision making processes. Agent-based approaches reproduce well market features, and work with frameworks that seem to make more intuitive sense when the functioning of real markets is considered. Agent-based frameworks can also be used as a testbed for drawing in behavioral results in experimental financial markets (LeBaron, 2006). By using this approach, limitations of traditional theory could be overcome (Jaramillo and Tsang, 2009). A system is evolutionary if its components or their properties change over time (Friedrich, 1984). In a financial market traders may adapt their behavior as they learn from experience. Evolution further applies to the kind of traders. Whereas about four decades ago5, trades were based on the incentive of human beings, today, a great share of trading volume is performed by computers. According to Johnson et al. (2003), evolution also implies the presence of extreme behavior; the dynamics of the system may evolve far from equilibrium and tend to show vigorous motions. Bubbles and crashes may be regarded as examples for extreme behavior in financial markets.

One reason why financial market dynamics prove so difficult to grasp and model is that they are driven by heterogeneous market participants' actions and interactions that feed back into the financial system. To understand how these complex systems evolve in time, an approach that has been very fruitful thus far is to consider the dynamics of a small number of aggregate collections of homogeneous variables. In this approach, the dependences of aggregate averages on other aggregate averages, and on time, are modeled by coupled systems of ordinary or partial differential equations. Moreover, a recent study shows that such a naive strategy can outperform more complex models. The majority of agent-based financial market models focus on price dynamics, which emerge through the interaction of heterogeneous agents. Such models have been quite successful in replicating and explaining some intriguing features of the financial market, such as endogenous bubbles and crashes as well as stylized facts of return time series including fat tails and clustered volatility. Compelling reviews of the literature can be found in LeBaron (2006), Hommes (2006), Chiarella et al. (2009), Hommes and Wagener (2009), Lux (2009), Hommes, (2011) and Zhou et al., (2014).

In this paper we discuss some ongoing tendencies in the recent literature on the interplay between Experimental Economics and Agent based Computational Approach. Our survey shows a gradual shift of the interest from the aggregate framework to the micro empirical structure, thus accounting for a "complete" heterogeneity in modeling agents' behavior. These features are usually absent in standard financial models but are at the heart of agent-based modeling. Agent-based models use the computer code rather than mathematical equations model description form, technically enables researchers to easily inquire into many interesting features of systemic behavior. However, theoretical or empirical foundation of individual agents' behavior and external validation of model results are two main problem areas, which have not been systemically addressed to date and constitute a serious obstacle to the further progress of agent-based financial modeling. The remainder of the paper is, therefore, organized as follows in order to connect each origin to its associated agent paradigm.

We start with the brief view of Artificial Stock Market in Section 2. Then we continue the tour with the majority of agent-based financial market models in Section 3, then move to the Agent-based Simulation Approaches in Section 4. Concluding remarks are then given in Section 5.

II. Recent Developments in Artificial Market Research

Artificial financial markets are models for studying the link between individual investor behavior and financial market dynamics. They are often computational models of financial markets, and are usually comprised of a number of heterogeneous agents, which interact through some trading mechanism, while possibly learning and evolving. These models are built for the purpose of studying agents' behavior, price discovery mechanisms, the influence of market microstructure or the reproduction of the stylized facts of real world financial time-series. Artificial markets are an emerging form of Agent-based social simulation in which agents represent individual consumers, firms, or industries interacting under simulated market conditions. Agents of various types may be combined within the same artificial market, such as simulated firms pursuing various strategies to increase their market share among simulated consumers. In this part we introduce two "classical" the most cited and the most used artificial stock markets, the Santa-Fe Artificial Stock Market and the Genoa Artificial Stock Market.

The Santa Fe-ASM is one of the most heavily cited, and one of the first sophisticated agent-based financial market models that applies a bottom-up approach for studying stock markets. The goal of the Fe-ASM is to understand the dynamics of relatively traditional economic models. It was originally designed to investigate the dynamics of a market in which bounded rational agents form endogenous expectations by means of inductive reasoning (Arthur, 1994). It helps study the emergence of trading patterns as agents learn over time. Investors base their orders on a set of strategies that evolves over time by means of genetic algorithms. Results suggest that the efficiency of the market and the performance of the traders depend on the speed with which traders update their set of strategies.

The Genoa artificial stock market was introduced in (Raberto et al., 2001). The main problem studied in the GASM is how the market microstructure and the macroeconomic environment affect market prices. In order to address this problem a multi-agent framework has been proposed using which it would be possible to perform computational experiments with various types of artificial agents (Raberto et al., 2001, Cincotti et al., 2005). The authors claim that this platform has been developed not as a standalone optimization application for present model, but as an evolving system able to be continuously modified and updated. For instance, the platform can be extended to an unlimited number of different kinds of securities, it can be used as an engine for a trading game and, moreover, for implementing real online trading.

The experiment, the simulated stock market model is tested on a single stock where the artificial active traders demonstrated strong learning abilities and dynamic learning behaviors. In this procedure of iteration, the artificial market will demonstrate the complicated self-adjustment simulation on the real stock market, where the typical simulation structure is shown in Fig. 1.

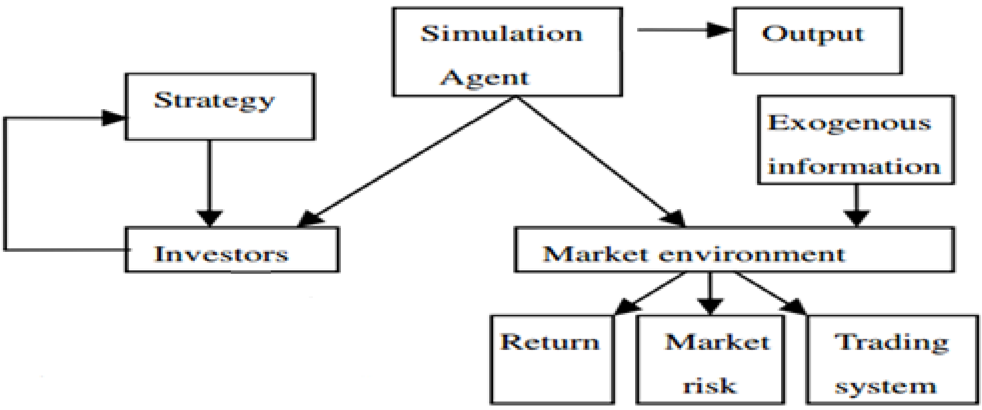

Figure 1 Structure of the artificial stock market

2.1 Organizational aspects of Artificial Stock Markets

Artificial stock markets are primarily designed with the aim to help us to understand and study market dynamics. Price formation mechanisms are basically order execution mechanisms, since market prices are formed as a result of executing orders. In order to find out how to design artificial stock markets an overview of the structure and workings of real stock markets is required. The most realistic way of modeling a system would be to represent every detail, to precisely implement its whole structure. Main factors that describe a market structure are (Haris, 2003; Boer, 2008).

Market participants

We classify different market participants in two main groups: investors and financial agents.

Investors are simple traders, who place public orders. Financial agents are traders endowed with special role in the financial market. There are several types of financial agents endowed with different tasks based on the market microstructure where they interact. In the exchange markets typically four types of financial agents interacts Reilly (2003):

- Commission brokers: are employees of member firms, who execute public orders as asked by the brokerage firm
- Floor brokers: are independent members who act as brokers for other members (because they are for example too busy)
- Registered traders or competitive market makers: are allowed to trade for their account, and provide added liquidity.
- Specialists: they serve as brokers for matching buy and sell orders, and to handle special limit orders; and further, they need to maintain a fair and orderly market by providing liquidity when the normal flow of orders is not adequate.

The number of different financial agents and the way they are allowed to trade is given by some market specific regulations. As the above described classification suggests, financial agents need to conduct basically two tasks: execute orders on behalf of the clients: broker specific tasks and execute orders for own account: dealer specific tasks.

Traded assets

The objects traded in a market are called traded instruments. Stocks, the instruments traded, are financial assets that represent ownership of corporate assets. LeBaron (2006) writes "Another very common and pertinent criticism is that most agent-based financial market models assume a small number of assets. Often agents trade only one risky asset, and one risk-free asset alone, this simplification may eliminate many interesting features". Furthermore, it usual to use assets to introduce some random variation into the market, this generally comes in the form of dividend payments. Palmer et al. (1994) found that autoregressive models most closely represented real dividend time-series.

Orders

When a person, a professional trader, a market maker or a corporation are trading on a stock market, there are different ways to do so. After the decision making process of any of such entities an order must be submitted to a broker. Essentially, there are two main types of orders:

- Market order: Specifies size of the stock and type of the trade (buy/sell) for the trade.
- Limit order: In addition to the specifications of a market order, it specifies the length of order validity with respect to time or change in price.

The market orders are buying or selling orders that must be executed at the current price of the stock on the market. There is certainty about the execution of a market order but uncertainty about the execution price. On the other hand, limit orders are buying or selling orders in which the trader specifies the price at which she is willing to trade (such prices are called bid or ask prices). In the case of limit orders, there is certainty about the execution price, but there is no certainty about the execution of the order.

Trading Sessions

According to time the market models can be divided between discrete and continuous. Discrete: Occurs at well specified time. During a call, all the trade requests are aggregated and a single price is set. Continuous: Trade can occur at any time when the market is open. In discrete models, time advances in discrete increments, while in continuous models the system changes continuously over time. Most agent-based artificial stock markets are organized as discrete-time models (Brock and Hommes, 1997; Challet et al., 2005).

Calibration and validation

While agent-based models are able to represent the market structure and trading rules in a very realistic manner and are capable to reproduce many real market patterns, most models may be not easily calibrated to real-world data. Calibration consists in setting parameters to help the model best fit empirical data, while validation consists in verifying the hypothesis about the ability of the model to fit real data. Validation is needed to select the model which best fits real market data or data properties. An agent-based model is validated if the generated data and the real data belong to the same distribution. Calibration methodologies are necessary and crucial in validation.

Stylized Facts

It is by now well known that the economic time series of almost all financial assets exhibit a number of non trivial statistical properties called stylized empirical facts. No completely satisfactory explanation of such features has yet been found in standard theories of financial markets, but more than fifty years of empirical studies their presence. For a complete discussion about stylized facts and statistical issues Cont (1997); Cont et al. (1997); Farmer (2005); Bouchaud (2000); Cont (2001) and Mantegna and Stanley (2008). There is a set of stylized facts which appear to be the most important and common to a wide set of financial assets: unit root property, fat tails and volatility clustering.

2.2 SWOT analysis

Garcia (2005) concur that artificial markets constitute an especially strong venue for studying technology diffusion, where complex social interactions limit the usefulness of equation-based forecasting techniques like the Bass model. The author conclude that artificial markets show great promise for exploring innovation dynamics, for analyzing massive market data sets, for generating and evaluating business strategies in volatile markets. However, artificial markets overcome several weaknesses and threats in the areas of agent specification, calibration and analysis. In this subsection we explore the strengths, weaknesses, opportunities, and threats facing artificial markets as they pertain to technological innovation research.

Strengths

Artificial markets belong to the causal or explanatory class of models in which the relevant variables and linkages are endogenously specified in terms of mathematical equations or simulation code. Models of this class are often used to forecast technology adoption and diffusion (Martino, 1999). The strengths of artificial markets may be better understood by contrasting the agent-based approach with a second member of this class, system dynamics models. Edwards et al. (2003) compared an individual-based model of innovation diffusion with its aggregate equivalent and found that while the two approaches sometimes arrived at the same conclusions, at other times they did not. They found the distinguishing factor to be the degree of behavioral complexity exhibited at the individual level: when individual behavior is simple, the results are more likely to converge; when individual behavior is complex, the results are more likely to diverge.

A particular strength of artificial markets is their ability to endogenously represent psychological variables; consumer psychology has been largely overlooked by previous diffusion studies (Gatignon and Robertson, 1991; Kottonau et al., 2000). The forte of artificial markets occurs in demand-side forecasting situations when social interaction and/or cognitive biases are known to be important, when consumer behavior is complex and market behavior volatile (Garcia, 2005; Adjali et al., 2007), when equation-based modeling would impose too many restrictions, and when controlled experimentation is desirable yet infeasible. These conditions are typical of innovation diffusion (Johnson, 2008).

Opportunities

We identify several additional promising applications, as well as, market forecasting, exploring market dynamics and innovation mining of artificial markets in technological innovation research. In the one hand, market forecasting has already been noted that artificial markets are finding practical applications in the area of innovation diffusion when alternatives such as the Bass model are infeasible (Janssen and Jager, 2003). Also, artificial markets could be used to simulate how markets might respond to innovations under various conditions, enabling managers to explore 'what if' scenarios before making major resource commitments. In the other hand, the hypothetical 'innovation mining' application, an artificial market could be constructed of a target city or region to reflect the demographics, social networks, adoption status, and preferences of the target consumer population. Scenario analysis could also be used to interpret future market states predicted by the artificial market and nominate leading indicators of these states for validation and tracking purposes. The relative probabilities of these states could be estimated with additional simulation runs, after which the results could be fed into normative decision support models.

Weaknesses

The weakness of artificial markets in finance is summarized in (Tefatsion and Judd, 2006). Critics point out that numerical results have errors. But these errors can be anticipated by the application of sophisticated algorithms and powerful hardware. The problem of numerical errors in agent-based computational models is no more difficult to handle than the analogous numerical problems that arise in maximum likelihood estimation and other econometric methods. Researchers face a trade-off between the numerical errors in computational work and the specification errors of analytically tractable models. Human behavior is complex, and agents are difficult and time consuming to construct. The challenge is how to specify consumer behavior rules which are realistic and accurate without burdening the model with excessive complexity (Jager, 2007). Agent-based model should allow agents to evolve, to act and to interact with others overall experiment time without intervention from the modeler. The modeler cannot intervene to adjust system evolution.

All initial specifications should be completely predefined; small changes in these specifications can significantly affect the output. The model should have the right parameters for the simulation to make sense. Therefore, sometimes it is difficult to justify the value taken for some parameters. It is entirely possible to use empirical data to calibrate an artificial market but not to specify it. Calibration is a challenging task (Drogoul et al., 2002; Fung and Vemuri, 2003; Garcia et al., 2007; Louie and Carley, 2008). Data may be difficult to acquire or measure directly, and in their absence the model parameters may only be estimated (Goldspink, 2002). New techniques are needed to support model verification and validation, sensitivity analysis, output analysis, system comparison, and visual representation of results. In particular, research is needed on how to validate findings generated by artificial markets (Midgley et al., 2007; Louie and Carley, 2008).

Threats

Artificial markets also face threats which arise from fundamental, exogenous limitations rather than the internal attributes of the Agent-Based Simulation method. Socio-technical systems are notoriously difficult to forecast; predictions are usually qualitative and very often inaccurate (Ascher, 1978; Porter et al., 1991). Forecasting problems arise in part because socio-technical systems exhibit sensitivity to initial conditions which limits the usefulness of historical data (Linstone, 1999). Some have argued that sensitivity to initial conditions effectively rules out prediction, at least for complex nonlinear systems involving deterministic chaos. However, sensitivity to initial conditions is a function of the system structure. Complex nonlinear systems may be extremely sensitive to certain types of change, while highly stable in regard to others. Thus, while AMs could not be expected to predict which specific design would win, they could be used to assess the probability that the eventual winner will exhibit certain key characteristics that follow as a natural consequence of the environmental conditions. Several key traits of artificial markets are summarized in Table 1.

Table 1 Key characteristic of artificial markets

Key idea	Artificial markets: agent-based simulations of market behavior.
Typical areas of variability	Abstraction vs. realism; agent interaction mechanisms; agent heterogeneity; the role of randomness; cognitive complexity of agents.
Strengths	Simultaneous expression of multiple variables of demand-side markets; controlled 'what if' experiments on complex market behaviors.
Opportunities	Diffusion forecasting; exploring innovation dynamics; education and insight; massively parallel market analysis; assessing business models in volatile new markets.
Weaknesses	Currently unsolved problems in the areas of specification, calibration, analysis, publication, and replication.
Threats	Sensitivity to initial conditions; plasticity

III. Varieties of agents: Simplicity, intelligence, and randomness

The majority of agent-based financial market models focus on price dynamics, which emerge through the interaction of heterogeneous agents. Such models have been quite successful in replicating and explaining some intriguing features of the financial market, such as endogenous bubbles and crashes as well as stylized facts of return time series including fat tails and clustered volatility. Compelling reviews of the literature can e.g. be found in LeBaron (2006), Hommes (2006), Chiarella et al. (2009), Hommes and Wagener (2009), and Lux (2009). Agent-based modeling is characterized by the existence of many agents who interact with each other with little or no central direction (Axelrod, 2003).

Computational study of these dynamical systems of interacting agents is what agent based computational finance is all about. Let us very briefly discuss the principal attributes of the research object of agent-based financial models. Naturally, at the centre-stage are agents. Agents, in this context, are given quite a broad meaning. According to Tesfatsion (2006), they comprise bundled data and behavioral methods representing an entity in a computationally constructed environment. They can range from active, learning and data-gathering decision-makers, their social groupings and institutions to passive world features such as infrastructure. From the operational point of view, they are similar to objects and object groups in the object-oriented programming, whereas agent-based models technically are collections of algorithms embodied in those entities termed "agents". The possibility to develop composite and hierarchical structures of computational agents implies that they can become arbitrarily complex and may greatly surpass their analytical counterparts of standard models in respect of reflecting salient features of the real world entities. The interdisciplinary nature of the notion of an agent also leads one to the realm of the computer science. Here, an autonomous agent is understood as a system situated in, and part of, an environment, which senses that environment, and acts on it, over time, in pursuit of its own agenda. If agents are capable of learning to achieve their goals more efficiently or their population as a whole continuously adapts to be better suited to survive, the artificial intelligence theory comes into play. Learning and adaptation are crucially important in agent-based modeling since the ultimate goal of any economic analysis is to model the actual human intelligent behavior and its consequences at the individual or aggregate level.

We now attempt to put the several ideas of agents discussed so far together and look more closely at their relationships, which may otherwise be largely taken for granted in many applications. We start with the idea of simple agents or agents following simple rules (automata), then agents with low-cognitive capability (zero-intelligence agents and artificial ants), and finally end up with randomly behaving agents and entropy-maximizing agents. The basic question is: are they the same? We have this question simply because in many applications they are assumed to be so. However, here, what we encounter is exactly an example of the agent as an interdisciplinary concept, and the terms, such as ‘‘simple’’, ‘‘naive’’ and ‘‘random’’, cross several disciplines, from computer science, psychology, and neuroscience, to mathematics and physics. Can these different terms or concepts belonging to different disciplines be unified on a higher ground, or are they independent? In the following, we shall reflect up on each of the three bilateral relationships as depicted in Fig. 2.

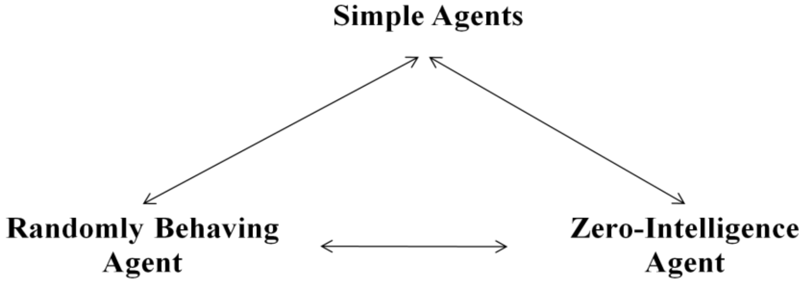

Figure 2 The different notions of agents

3 Agent-based Simulation Approaches

3.1 Pure Agent-based Simulation: The Bottom-up Approach

Agent-based computational economics has received increased attention and importance over recent years. Some researchers have attempted to develop an agent-based model of the stock market to investigate the behavior of investors and provide decision support for innovation of trading mechanisms. The goal of agent-based modeling is to enrich our understanding of fundamental processes that may appear in a variety of applications. The emergent properties of an agent-based model are the result of “bottom-up” processes, rather than a “top-down” direction (Axelrod, 2003). While the topics being investigated by the agent-based approach may be complicated, the assumptions underlying the agent-based model should be simple. The complexity of agent-based modeling should be in the simulated results, not in the assumptions of the model (Axelrod, 2003).

He studies spatial arrangements where agents of different characteristics prefer to live in a neighborhood of a certain characteristic, e.g. the color of the neighbors. Agents have preferences that at least a particular fraction of the neighborhood has their own color. Changing these preferences certainly leads to different compositions of the neighborhood. In what is denominated the pure agent-based approach, the model consists of several agents, the environment the agents act in, and interaction rules. These interaction rules are fixed for the agent, meaning that the agents’ action sets are not changed, as it is the case if using learning mechanisms such as reinforcement learning or genetic algorithms. Arthur (2006) presents a very simple but striking example that explains the model dynamics by changing fixed interaction rules: In a group of agents each agent is assigned a protector and an opponent randomly and secretly. Each agent tries to hide from the opponent behind the protector.

This simple rule will result in a highly dynamic system of agents moving around in a seemingly random fashion. Changing the rule in such a way that the agents have to place themselves between opponent and protector, the system will end up in everyone clustering in a tight knot. This example shows how simple rules result in complex dynamic systems. Arthur (2013) incrementally developed Sugars cape, a model of a growing artificial society that received much attention in the agent-based research community. Agents are born into a spatial distribution, the Sugars cape. Agents have to eat sugar in order to survive and thus, move around on the landscape to find sugar. Starting with simple movement rules, more and more social rules like sexual reproduction, death, conflicts, history, diseases, and finally trade are introduced. This results in a quite complex society that allows to study several social and economic aspects.

As a last example may serve the computational market model that builds a small society of agents that can either produce food or gold. Each agent needs food for survival and is equipped with a certain skill level of producing gold or food. Food can be traded for gold. In such a simple model, agents switch from producing food to gold or vice versa if the exchange rate passes their individual level from which on it is more lucrative for them to produce the other product. This results in cyclic trade behavior with large amplitudes of volume and price. When adding speculators, agents that have the capabilities of storing gold and food, the price stabilises significantly. A novel bottom-up approach to studying and understanding stock markets comes from the area of computational finance as artificial financial markets (or, more specifically, as artificial stock markets). Agent-based artificial financial markets can be mathematical or computational models, and are usually comprised of a number of heterogeneous and boundedly rational agents, which interact through some trading mechanism, while possibly learning and evolving (Urquhart and Hudson, 2013, Zhou and Lee, 2013, Zhou et al., 2014, Ghazani and Aragli, 2014, Verheyden et al., 2014 and Hull and McGroarty, 2014).

Agent-based approach is an answer to highly centralized, top-down, deductive approach that is characteristics of mainstream, neoclassic economic theory. Most of the time, the neoclassic approach favors models where agents do not vary much in their strategies, beliefs or goals, and where a great effort is devoted to analytic solutions. By contrast, agent-based modeling considers decentralized, dynamic environments with populations of evolving, heterogeneous, bounded rational agents who interact with one another.

3.2 Monte Carlo Simulation

In general, the term Monte Carlo denotes methods for mathematical experiments using random numbers. Monte Carlo Method The only reasonable option to computationally examine the impact of suggested changes on the model outcomes is to perform simple Monte Carlo simulations (Rubinstein and Kroese, 2008). Within this method, we repeatedly stochastically generate crucial variables using different random number generator settings and consequently run the model employing generated values. All the simulated data is then put together and this sample represents the “true” distribution of model outcomes. The sufficient number of runs is therefore very important to obtain statistically valid and reasonably robust sample.

Research applying microscopic simulations in economics and finance stems from several sources. First, a number of authors in the economics ‘mainstream’ have resorted to some type of microscopic simulation in the course of their work on certain economic problems and models. Kim and Markowitz (1988) decided to investigate the destabilizing potential of dynamic hedging strategies via Monte Carlo simulations of a relatively complicated model of price formation in an ‘artificial’ financial market.

The problems studied by Monte Carlo methods can be distinguished in probabilistic and deterministic problems. Probabilistic problems determine cases where random variables are used to model real stochastic processes, e.g. in queuing theory. One speaks of deterministic Monte Carlo cases if formal theoretical models exist that are not possible or hard to solve numerically. In agent-based simulation, Monte Carlo methods are used for both, probabilistic and deterministic, models. In most of the agent-based simulation models, probabilistic Monte Carlo methods are applied to assign valuations to agents, or to simulate noise. A well known example is the contribution of Rubinstein and Kroese (2008) in which a double auction market is simulated by agents with zero intelligence. Instead of implementing fixed strategies, agents in this market draw their bid value from uniform distributions regardless of true valuation. This strategy is used to represent bounded rational agents.

3.2Evolutionary Approach

In order to deal with the problem of very complex heterogeneity, which leaves the boundary of what can be handled analytically, some researchers decided to abandon the goal of analytical tractability and to embrace a complete evolutionary approach. The most influential project in this respect is the Santa Fe artificial stock market (Arthur, 1994, 2013) developed in the early 1990’s. This simulated market bypasses some pitfalls of the representative agent approach by endowing agents with non-trivial capabilities: the actors have an internal representation of the world and can try to figure out the best optimizing model through continuous testing of alternative demand rules. Agents do not need to share information (other than price) and, when intensive learning is assumed, the market exhibits a complex behavior where even technical trading can be profitable in the short-run.

This body of recent literature variously support the claim that heterogeneity of agents can produce endogenous price fluctuations with the same statistical features of financial time series. These heterogeneous agents market models can be classified with respect to how they describe trading strategies and learning algorithms of agents. Up to now, however, the literature on artificially simulated financial markets has only rarely addressed an explicit modeling of the market microstructure, favoring instead unrealistic approximating devices for the price formation mechanisms like some sort of Walrasian auctioner or market maker with unbounded liquidity.

Financial time series are probably the most studied time series by numerous disciplines and Computer Science could not be the exception. Moreover, there is a growing acceptance among practitioners of the techniques and tools based or inspired by some important areas of research in Computer Science. Artificial Intelligence in general and Evolutionary Computation in particular are two of the most influential areas involved in the design of techniques and tools to perform some forms of financial forecasting. Among the most successful ones we can find Artificial Neural Networks, Genetic Algorithms, Genetic Programming and Learning Classifier Systems.

Evolutionary computation approach possesses now a long tradition as a research tool in economics and particularly in finance. The areas of research in economics and finance, in which an evolutionary technique is being used, are among the most relevant ones in both fields. It is not exaggerated to say that evolutionary computation is at the heart of economics and finance, sharing the place with more traditional tools. In finance, evolutionary computation has a long lasting tradition, for example; Arthur, (2006), Velupillai and Zambelli (2011) and Chen (2012). Despite the existence of several useful artificial intelligence techniques like neural networks, a great body of research in computational economics and computational finance employs some form of evolutionary computation. In the following subsections, some examples of such applications will be provided and some of the most relevant works are going to be briefly described. It would take a full survey paper to give a complete account of all the work that has been done in economics and finance using evolutionary computation.

IV. Conclusion

An artificial stock market characterized by heterogeneous and interacting agents has been studied. In this complex system, agents are characterized by cash, stocks and sentiments. In this research, by developing diverse ideas with the designing of artificial agents as the key thread, we try to present one style in the review of agent artificial market. We give a short historical review of agent-based computational approach by tracing markets, artificial agent and further to economic experiments. Agent-based artificial stock markets can facilitate the understanding of the relationship between individual investor strategy and aggregated market phenomena, by allowing the modeler to specify the investor behavior, to implement different market microstructure, and to analyze the resulting asset prices. In such a way, the artificial stock market can help investigate the scenarios for which empirical data do not exist, or are difficult to obtain. In this context, we would like to close this survey with some speculations regarding the future. The idea of human-like agents has been recently pursued quite intensively by the agent community, which is mainly computer science-oriented. Various models of agents with personality, emotion and cultural backgrounds have been attempted. This research trend has been further connected to computational models of the brain, neuroscience and neuroeconomics. To what extent agent computational economics can benefit from this enlarging interdisciplinary integration of agent research, an open mind is required.

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