Investigating the Role of Social Behavior in Financial Markets through Agent-Based Simulation

(Extended Abstract)

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ABSTRACT

An evolutionary agent-based model inspired by the adaptive market hypothesis is used to investigate the link between the microscopic parameter of sentiment and market price movements. Agents model cognitive and social behaviors by means of rules wired into their decision-making models and of parameters encoded in their genome. Results show that co-evolution and social interaction among traders are responsible for bubbles and crashes.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems*; I.6.5 [**Simulation and Modeling**]: Model Development; J.4 [**Social and Behavioral Sciences**]: Economics

General Terms

Algorithms, Economics

Keywords

Agent-Based Simulation, Emergent Behavior, Co-evolution, Complex Systems

1. INTRODUCTION

Agent-based modeling [7], has become a widely accepted tool for studying the dynamics of financial markets [2].

While usually agent-based models of economies rely on very simple agents, which make them resemble interacting particle systems we wanted to investigate the use of richer, more sophisticated agent types, that more closely reproduce the characters of the participants in real-world economies, namely people. Previous work by the authors [1] added more realism in the way agents are modeled in agent-based simulations of financial markets by using cognitive agents and a real-world auction mechanism as the basic ingredients for the simulation, coupled with an evolutionary algorithm (EA) responsible for the adaptation of agent behaviors. The agent-based model we used for this study is an adaptation of that work.

An important reason to include the concept of evolution in a model that aims at achieving realism is that this idea is perfectly in line with the adaptive market hypothesis [5] (AMH), an attempt to reconcile the efficient market hypothesis with a growing number of criticisms leveled against it by psychologists and behavioral economists. According to the AMH, the markets would be in a perennial unstable equilibrium and, as their participants must evolve against each other, in constant flux.

The purpose of our work was to replicate complex phenomena like price bubbles emerging from the interaction of co-evolving, cognitive agents acting mostly rationally but with possible undertones of irrationality.

2. MARKET STRUCTURE

We used a realistic, albeit simplified, market structure: a single *asset* is traded on the market as a commodity against the payment of *money*. No transaction fees are claimed by the market and no expenses are payable for the storage and transportation of the asset.

Agents participate in the market by submitting buy or sell orders. The orders are matched by the market with a single-price auction every time a new order is received. An agent's *net asset value* (NAV) is the primary indicator of its performance.

Agents operate in a regime of incomplete information, in that every agent knows its current money balance and asset inventory, as well as the orders it submits, but cannot directly observe neither the orders entered by the other market participants, nor the balance and inventory of its peers. Instead, to determine their behavior, the agents have access to a set of technical indicators made available by the market and to the *sentiment* of other agents in their social neighbourhood.

Every given number of periods, a generation of the EA is performed, allowing the agent population to evolve towards more profitable behaviors.

3. AGENTS AND SOCIALITY

The agents model a combination of knowledge, experience, and psychology aimed at giving an outline of those decisional factors that are distinctive of human traders. All the agents share the same architecture, comprising two modules: a decisional module, inspired by neural networks [3], and an

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operational module, inpired by particle swarm optimization algorithms [4]. The decisional model generates the kind of order to be sent to the market based on beliefs, cognitive inertia, and current money balance and asset inventory. Beliefs are formed based on technical indicators, weighted by each agent according to a genetically determined individual degree of confidence; cognitive inertia is a kind of intention persistence; knowledge of the current money balance and asset inventory causes the agents to target an ideal balance. Agents are part of a social network determined by their genealogy. Each agent takes into account the decisions made by its close relatives, weighted by their genetic similarity and financial success. From such network arises the herd behavior, a self-organised pattern which is actually typical of real trader groups and is expressed by market *sentiment* on a macroscopic level.

Finally, the operational module defines the specifics of the order to be submitted to the market, namely the asset quantity and proposed bid or ask price.

A salient feature of the agents in this model is that they are evolutionary, i.e., they are the individuals of an EA. Therefore, every agent has a *genome*, in practice a set of 43 parameters that influence the way the agent reacts to stimuli from the environment. These genetically determined parameters do not change during the agent's entire lifetime, whereas the agent's mental state may change in response to changes in the market and in the agent's financial conditions.

An EA essentially following the general principles of the one proposed in [1] for the same purpose is used by the simulator to make the agents participating in the market evolve according to their trading proficiency. The EA proceeds concurrently with the trading activity in the market. A generation is performed at regular intervals, whose length, l, measured in trading periods, is a parameter of the simulation. The fitness of an agent is given by its NAV. At each generation, the 30% of the individuals having the lowest NAV is eliminated from the simulation, and their wealth is redistributed to the remaining 70%, which undergoes fitness-proportionate selection, crossover, and mutation. New agents inherit their wealth from both parents.

Social networks are an important base of real economies. Herd behavior is the kind of sociality that was reproduced in our model. It has been argued that this kind of behavior determines bubbles and crashes [6].

Our agents are influenced in the trading decisions by the sentiment of their social the neighbourhood in a way that makes them imitate their successful relatives, with the exception of those that have not made proof of good trading skills. To allow us to study its effects, sociality may be turned on and off.

4. EXPERIMENTS AND RESULTS

To study the relationship between herd behavior and price dynamics, we introduced an exogenous shock to the market, consisting in sudden changes of the interest/dividend paid by the asset or the money. As it can be observed in Figures 1 and 2, sociality emphasizes and amplifies market reactions to shocks.

A bubble grows when returns are distributed on assets in simulations with sociality turned on. On the other side, the bubble crashes when returns are shifted to money and traders loose interest on the assets. This does not happen when sociality is turned off.

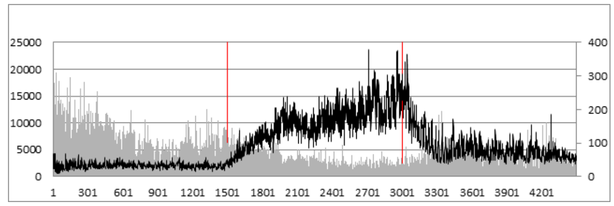

Figure 1: A shock applied to a simulation with sociality turned on.

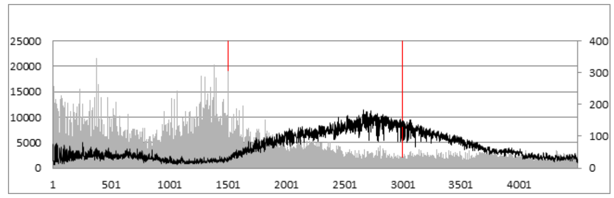

Figure 2: A shock applied to a simulation with sociality turned off.

Through the evolutionary process, only the agents who are able to gain wealth can survive. The evolution leads to a system in which the agents adopt complementary market behaviors keeping the market in an unstable equilibrium. If the EA is turned off, even at a stage when well-adapted trading strategies have emerged, all trading activity wanes and comes to a grinding stop after a few periods. We have observed that agents showing extreme behaviors do not manage to survive and moderate behaviors of the conservative kind tend to become commonplace in a co-evolved population.

5. CONCLUSION

We have studied and analized the effect of social behavior in financial markets by means of an evolutionary agent-based model, finding evidence that herd behavior is responsible for emergent phenomena like bubbles and crashes.

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