AN ADAPTATIVE EVOLUTIONARY MODEL OF FINANCIAL INVESTORS

Boldea Bogdan Ion
West University of Timişoara,
Faculty of Economy and Business Administration,
Str. J.H.Pestalozzi, no. 16, 300115, Timisoara,
E-mail: bbi77@yahoo.com
Boldea Costin-Radu
University of Craiova, Faculty of Mathematics and Computer Sciences, Str. A.I.Cuza, no. 13, cod. 200585, Craiova, E-mail: cboldea@inf.central.ucv.ro
Stanculescu Mircea
"Spiru Haret" University, Faculty of Management and Accounting, Str.Brazda lui Novac, no. 4, 200585, Craiova E-mail: mircea.stanculesscu@yahoo.com

The main purpose of the paper is to determine a general behavior of a multi-agent model capable of describing the process of deliberation of an investors group witch may repeatedly decide whether to buy or sell an asset. Each adaptive agent was modeled as a collection of strategies which is optimized by an evolutionary algorithm (EA). The paper investigates the implications and the effect of the learning process for the information strategies used by the agents in the process of deliberation of buy and sells order.

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1.INTRODUCTION

Behavioral traits of market participants and their effects on the properties of markets have been under growing investigation in recent years. Much of this work (e.g. [3], [4], [5], [6] and [8]) which emphasizes deviations from efficient markets theory, tries to elicit an internal market dynamics via computational approaches, and is loosely linked to the subject known as behavioral finance. These interdisciplinary studies try to explain market phenomena by formalizing a diverse array of behavioral and psychological considerations. Shiller, [11], strongly argues against a priori excluding any behavioral information from the explanations of financial markets.

An agent-based approach contains a model for individual behavior combined with a price formation rule. Despite great emphasis on the characteristics of real market participants, however, models of individual behavior have remained rather simple. In an agent-based model, an agent's psychology as distinct from manifest behavior is often not separately represented. Further, an agent is often modeled as a unit capable of being in one of a small number of states.

We used a multi-agent model capable of describing the process of deliberation and how it leads to action. In our model, each agent is described by an internal state with an intrinsic dynamics and influenced by external events within or outside the population of agents. Actions result when the agent's state crosses a predetermined threshold in state space. Specifically, we consider a population consisting of investors repeatedly deciding whether to buy or sell an asset.

Each adaptive agent was modeled as an informational strategy which is optimized by an *evolutionary algorithm* (EA) ([1], [10]). EAs transfer the principles of natural evolution, first discovered by Darwin, to a computational setting. These algorithms have been used in the past, with considerable success, to solve difficult optimization problems (Bäck [1]). Adaptive agents learn in different ways in an evolutionary setting: by selection and reproduction of successful strategies, and by random experimentation (by "mutating" existing strategies) or by recombining or "crossing over" previously-tested strategies.

The main purpose of the paper is to determine a general behavior of the model system described before by evolutionary simulation. In the spirit of genetic algorithms methods, we classify the result of a simulation in group of strategies efficiency. A secondary important goal it will be to find some stable states of the system, states who generate a description of the wining strategies of the agents.

2.THE MODEL OF INVESTORS BEHAVIOR

2.1. Single investor mathematical model

Here we try to quantitatively capture a simple, perhaps superficial, part of a financial agent's psychology as well as its connection to actual behavior. This is kept to a bare minimum in order not to obscure our general approach. The model is based partly on results of so-called neural decision field theory (Ormutag, Knight and Sirovich [9]), adapted for financial investors.

We assume that the state of an agent at time **t** is fully determined by the value of a variable x(t). This is the agent's momentary internal condition. It may be viewed, in general, as the agent's disposition or tendency to behave in a number of specific ways. 'x' determines the coordinates of state (or phase) space where each agent is represented as a point. The agent acts only when its representative point crosses a predetermined boundary or threshold in state space. More specifically we consider an investor repeatedly faced with the problem of deciding whether to buy or sell a particular asset. The agent's ongoing process of deliberation is described by the dynamical system

$$\frac{\Delta x}{\Delta t} = -\gamma x + I(t) \tag{1}$$

where **γ** is the personal decision reaction speed, supplemented by the condition that at |x| = 1 the state is reset to x = 0. The reset condition constrains the state to remain within a finite interval, −1≤x≤1. The function I(t) describes the effect of external influence on the agent. This may originate from all kinds of sources information such as the news media or personal contacts. Note that, despite appearances, (1) is non-linear, due to the reset condition. If we regard x as the fraction of certainty in buying/selling, then the choice of ±1 as thresholds appears less arbitrary.

The effect of external information arrival was reprezented by a series of instantaneous jumps of size **e**(k) in the state received at arrival times t_k, *k = 1, 2, …*. This formulation is valid so long as the time scale of the impact of information is much shorter than that of other changes in x. The agent's state is therefore driven by a term

$$I(t) = \sum_k e(k)\delta(t - t_k) \tag{2}$$

where the sum is from the last moment of reset condition (the last buy or sell action) until the curent time *t.* It will be assumed the existence of a large number of uncorrelated sources of information and accordingly take arrivals as being Poisson distributed in time. For simplicity each jump will be taken as positive, $\mathbf{e}_+$, or negative, $\mathbf{e}_-$. Following this formulation, we will refer below to positive and negative pieces of information. Generalizations to jumps with stochastic size or jump size which depends on the current state are straightforward. We take the magnitudes $\mathbf{e}_\pm$ as measures of *informational impact* on a typical agent. In the special case of $\mathbf{e}_+=-\mathbf{e}_-$, one can speak of informational impact being symmetric. The informational impact magnitudes $\mathbf{e}_\pm$ *describes the informational strategy of the agent and characterize it*.

In this model the dynamics of the state leads to action in the following way: the agent places an order to buy (sell) when its state crosses the boundary at *x*=1 (respectively −1). Accordingly, when *x(t)* is in the positive (negative) half of the domain, the agent has a greater tendency to buy (sell) and may be viewed as being "optimistic" ("pessimistic").

2.2. Interactions

We next consider a large collection of N agents trading the same asset. Each agent is indexed by i = 1,...,N, and its state described by the equation (1). Market participants clearly do not collectively listen to the same news and are not exposed to the same channels of information, then inter-agent differences in exogenous information are to be expected. In our model we allow every agent ***i*** to be driven by its private stream of information $\mathbf{I_i(t)}$. Informational heterogeneity along with nonlinear dynamical evolution and possibly different initial conditions, injects a great variety of individual behaviors into the population.

The average rate of arrival of exogenous information is the same for all agents. Every agent, in addition, is affected by the behavior of other agents in the population. We denote by ***n*** the average number of agents affecting any one agent. Hence mutual interactions in the population occur through the influence of the actions of agents on the states of other agents. Specifically, if an agent places **i** an order to buy (resp. sell) at the moment $\mathbf{t_k}$, the state of another agent **j** is instantaneously incremented by eji+(−)(k) if that agent is affected by the action at that moment. The stream of information characterising the agent j at the time t will be

$$I_j(t) = \sum_k \left(\sum_{i=1}^{N} e_{ji}^{+(-)} \delta(t - t_k) \right) \tag{3}$$

Note that the $\mathbf{e_{ji}}$ term mesure the influence of the actions of agent **i** on the agent **j** and was taken sub-unitary. This formalizes the intuition that the more an investor sees others buying (selling) the more bullish (bearish) he or she will become.

3. GENETIC ALGORITHM: LEARNING AND SIMULATION

3.1. Evolutionary algorithms method

Genetic algorithms constitute a class of search, adaptation, and optimization techniques based on the principles of natural evolution. Genetic algorithms were developed by Holland ([7]). For an introduction to genetic algorithms, see Bäck, T. ([1]).

An evolutionary algorithm maintains a population of solution candidates and evaluates the quality of each solution candidate according to a problem-specific fitness function, which defines the environment for the evolution. New solution candidates are created by selecting relatively fit members of the population and recombining them through various operators. Specific evolutionary algorithms differ in the representation of solutions, the selection mechanism, and the details of the recombination operators.

Evolutionary algorithms offer a number of advantages over more traditional optimization methods. They can be applied to problems with a non-differentiable or discontinuous objective function, to which gradient-based methods such as Gauss–Newton would not be applicable. They are also useful when the objective function has several local optima.
More formally, the GA scheme can be summarized as follows. ***P*** denotes the current population (i.e., a set of individuals), and **H** is the set of children. Note ***g*** the current generation number. The Genetic Algorithm can be described by the pseudocode scheme:

```
g := 1;
generate initial population Pop;
compute fitness for individuals i ∈ Pop;
WHILE  g< G  DO
BEGIN
  g := g+1;
  produce children H  from Pop by crossover;
  apply mutation to children I∈  H ;
  Pop := Pop∪ H  ;
  compute fitness for entire population I∈ Pop;
  reduce population Pop by means of selection;
END.
```

3.2 Genetic Representation: coding the agents population and evaluating individuals by a 'fitness' function

For the multi-agent model described in the Section 2, a valid genetic representation is given by a vector of information's about the personal decision reaction speed $\boldsymbol{\gamma_i}$ and the coefficients describing the influence of the others agents $\mathbf{e_{ij}}$ (j=1..N):

$$(\boldsymbol{\gamma_i} \,;\, \mathbf{e_{i1}}, \ldots, \mathbf{e_{iN}}) \qquad (4)$$

At the start of the first generation of agents, each one of this is random generated between 0 and 1, with the supplementary condition that $\mathbf{e_{ij}=0}$, with the probability **p** (fixed from the beginning).
For evaluating the efficiency of individual agent information strategy, a simulation of the trade activity is necessary. We consider a trade game consisting in **m** rounds of negotiation ($t=t_k$, $k=1..m$). Each agent **i** start the simulation with a fixed capital $\mathbf{C_i(0)}$=10000 units. A buy/sell action of an agent modify his capital with a value equal with the price -/+ P_k of a market "action" at the time $\mathbf{t_k}$; alternatively, the price P_k is variable in time, according to the formula:

$$P_{k+1}= P_k(1+n_1(k)/N- n_2(k)/N) \qquad (5)$$

where $n_1(k)$ is the number of agents buying actions at the time $\mathbf{t_k}$, and $n_2(k)$ is the number of agents selling actions at the time $\mathbf{t_k}$. This condition simulates the variation of value of the price in condition of a free market. The *fitness* function associated to each agent is defined by the value of individual capital $C_i(m)$ at the time $\mathbf{t_m}$. At the tome t_0=0, the price was P_0=250 units.

3.3 Crossover, Mutation and Selection

Let us assume that two individuals of the current population have been selected for crossover. We have a mother individual $M=(L_M)$ and a father individual $F=(L_F)$. Now two child individuals have to be constructed, a daughter $D = (L_D)$ and a son $S = (L_S)$, each one by the *2-point crossover* procedure, choused to increment the speed of the algorithm.
For the crossover procedure we draw two random integers q_1 and q_2 with $1 \le q_1 < q_2 \le$ N. Now the daughter's activity list L_D is determined by taking the coefficient $\mathbf{e_{ij}}$ list of the positions $i = 1,...,q_1$ from the mother, the positions $i=q_1+1,...,q_2$ are derived from the father and the remaining positions $i = q_2+1, . . . ,J$ are again taken from the mother. The son individual is computed analogously. For the son's activity list, the first and the third part are taken from the father and the second one is taken from the mother.
The following *mutation operator* is applied to each newly produced individual. The mutation operator modifies the all the genes (including the coefficient of decision speed γ) of the genotype with a probability of p_{mutation}. The mutation operator modifies the value of a coefficient by a fixed fraction +(-)f (considered in the author simulation =1/10) of his initial value. The choice of sign is randomized.
The *selection operator* act on the entire populations of agents, the parents and the new agents, selecting at each generation the first N best evaluated individuals, grouped by pairs (first with the second etc.) in order to produce a new generation. The evaluation use the *fitness* function, computed after a trade game simulation.

4. COMPUTATIONAL RESULTS

In this section we present the results of the computational studies. The self-adapting GA for the RCPSP has been coded in Dev C++, and tested under Windows XP. We considered an initial population formed by N=50 agents, generated with the conditions $0<\gamma_i<1$, $0<e_{ij}<1$ and p=3/4 (the probability that $\mathbf{e_{ij}}=0$ at the beginning). The genetic algorithm computed G=250 generations.

First observation is that the simulation of the trade, at each generation, gives the possibility to evaluate the evolution of the market price P_t of one action in time. The Figure 1 give the evolution in time of the P_t for the resulting populations of agents after 250 generations. The similarity with a real chaotic market variation has a test value for the proposed model.

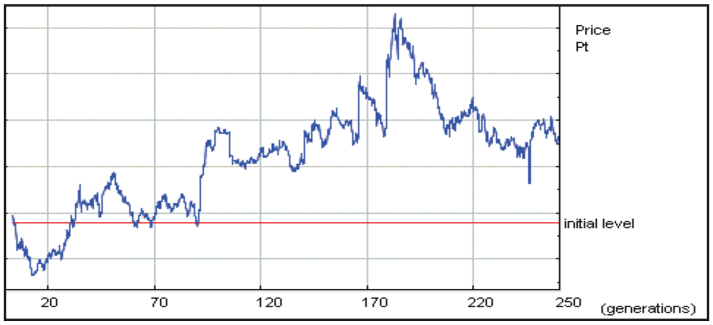

Figure 1. The market simulated evolution of the price of actions

The results reported in the Figure 2 are obtained after a process of learning, when the strategies have converged. It is important to note that, during learning, the number of significatives influences for each agent of new generation (i.e. number of agents **j** that influence an agent **i**, expressed by the condition $\mathbf{e}_{ij}\neq 0$) is increasing.

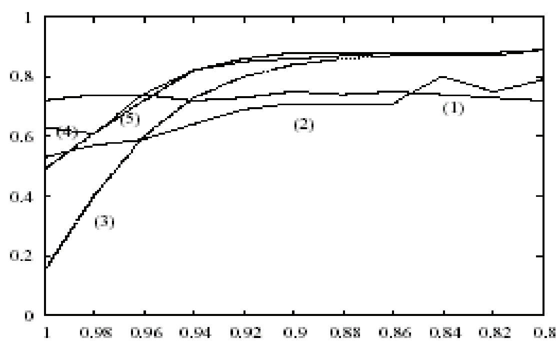

Figure 2. Statistical dependence of the information strategies efficiency of the relative number of sources

Five strategies are statistically identifiable:
- first (1) is the strategy of stability of the sources (the values of the influence coefficients $\mathbf{e}_{ij}$ are quite stable in time);
- the second (2) is a periodic strategy (generated by a quasi-periodical rotation of the trusted sources);
- the third (3) can be called the "mimetic" strategy (the temporary tendence of the market is reproduced bu the agent);
- (4) is a combination of (1) and (3);
- (5) is a combination of (2) and (3).

The Figure 2 show the statistical repartition of the 'fitness' for the final generation agent's strategies in dependence with the percent of the significative influence agents (reported at their total number). The 'fitness' value, measuring the efficiency of a information strategy, was reported to the best value obtained for all generations of agent's strategies.

5. CONCLUSION

In conclusion, the model described in this paper explicitly includes competition into a real options framework by using an agent-based approach of competing firms. The firms derive their investment triggers from a genetic algorithm which exploits the results of repeated stochastic simulations of the market. The best information strategies used by the learning trade agents under competition that we find are classifiable in five groups, and the mixed mimetic strategies are in top of efficiency. In other words, the combined strategy is very versatile.

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