A Study of Stock Market Trading Behavior and Social Interactions through a Multi Agent Based Simulation

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Abstract. In this paper, we study the stock market trading behavior and the interactions between traders. We propose a novel model which includes behavioral and cognitive attitudes of the trader at the micro level and explains their effects on his decision making at the macro level. The proposed simulator is composed of heterogeneous Trader agents with a behavioral cognitive model and the CentralMarket agent matching buying and selling orders. Our artificial stock market is implemented using distributed artificial intelligence techniques. The resulting simulation system is a tool able to numerically simulate financial market operations in a realistic way. Experiments show that representing the micro level led us to validate some stylized facts related to stock market and to observe emergent socio-economic phenomena at the macro level.

Keywords: Multi-agent based simulation, Cognitive and behavioral modeling, Trading agents, Stock market, Volatility.

1 Introduction

The complexity of financial market still represents a wide field of research and applications [2]. Empirical and numerical analyses of stock market are powerful; nevertheless they still insufficient [13]. Previous researches, such as in [9], are generally based on the hypothesis of rational behavior. We notice that the existing stochastic models have shown critical limits [22]. Therefore, emerged evidences show that stock markets could not be only studied with a rational paradigm [1]. In the last decade, we complete the description of theoretical phenomena by many aspects based on the traders' behavior and their interactions.

A study of the state of the art has given us the opportunity to illustrate the evolution of approaches studying the stock market and to identify the existing relationships between the major works. We interpret these relationships by a map shown in figure 1. We note that the list of considered works is not exhaustive. In this state-of-the-art map (figure 1), we consider two kinds of relation between woks: "*Inspire*" and "*use*". The link "Inspire" means that the original work affects and motivates the linked work. The link “use” means that the linked work employs the model proposed by the original work for some purpose via another approach. We distinguish an evolution of approaches used to study the stock market: (1) numerical approach during the eighties based on a stochastic modeling: [5], [10] and [15], (2) multi-agent based systems simulating stock market dynamics: [1], [9], [16], [17], [18], [19] and [21] and (3) behavioral multi-agent based systems in recent years: [12]. We note that psychological biases prevent traders from acting fully rationally and thus undermine the basic premise of the efficient market hypothesis [22].

The purpose of our paper is to study the stock market trading behavior and social interactions through a behavioral multi agent based system. This paper is structured as follows. In the second section, we describe the micro/macro level oh the stock market. First, we define a trader transaction protocol. Second, we detail the trader making decision and the behavioral attitude’s affects. Then, we represent social networks and interactions in our artificial stock market. In the third section, we expose the simulation and some results. Finally, in the fourth section, we conclude the paper and we summarize future works.

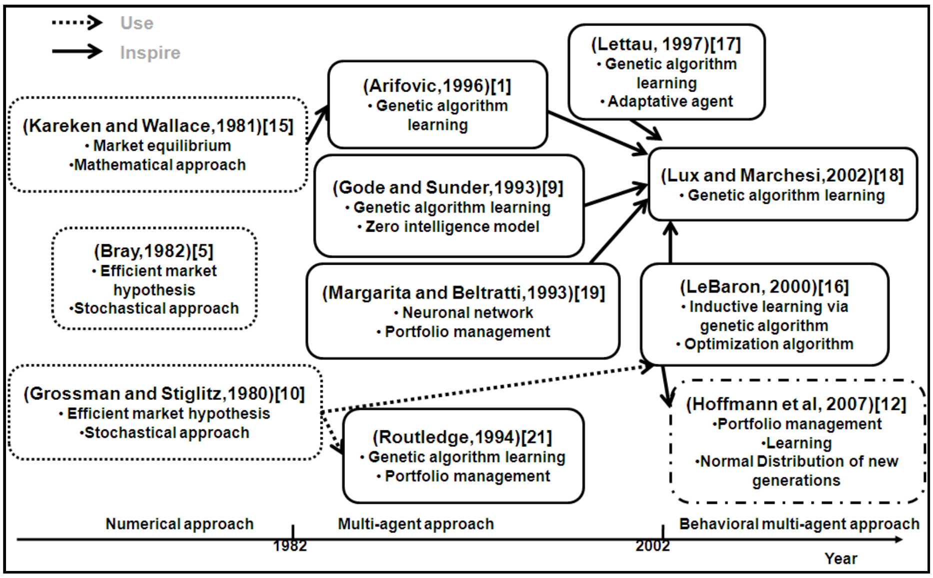

Fig. 1. The state-of-the-art map: Stock Market studies

2 The micro/macro level of the stock market

The agent approach [8] offers the possibility to model and to study two granularity levels of the stock market: the micro and the macro level. At the micro level, it gives the opportunity to observe the individual behavior of each trader. This approach allows to describe and to provide for each the basic mechanisms to decide for itself when, how and why a particular action must be made [6].

2.1 Trader Transaction Protocol

This paper introduces a novel model representing the stock market dynamics. Our artificial stock market includes the central market agent essentially responsible for executing transactions via an order book. It includes also a several kinds of trader agents depending to their profile. We take into account three pairs of behavioral attitudes: (1) Pessimism / optimism, (2) Speculation /Caution and (3) Mimetism / Leadership. In fact, trader decision making constitute a complex process which is based on cognitive and rational paradigm and biased by behavioral attitudes [23].

Interactions between traders and information's exchange during a transaction reproduce the market dynamics and organize the multi-agent based pricing. We adopt an approach based on the notions of Agent, Group and Role (AGR) [11] for the representation of our organizational model. Our artificial stock market is composed of: (1) a set of agents corresponding to the considered two types of actors: *ExpertTrader* agents and *NoviceTrader* agents, (2) a *CentralMarket* agent responsible of conducting transactions and controlling the dynamics of the stock market.

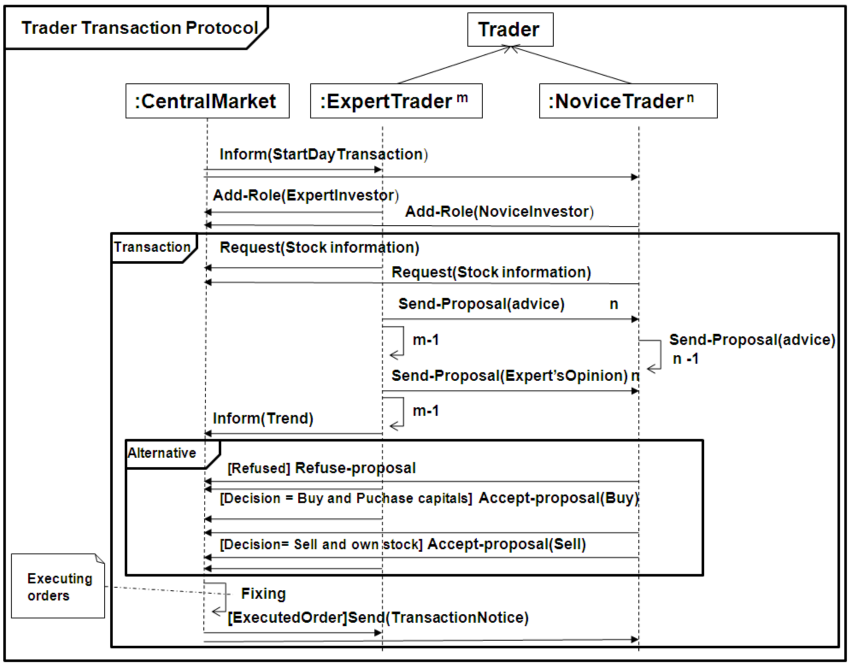

Fig. 2. Agent UML sequence diagram: Trader transaction protocol.

Figure 2 shows the Trader transaction protocol via an Agent UML sequence diagram. It specifies the sequence of messages that are exchanged along with their corresponding event occurrences on the actors' lifelines of our artificial stock market. Our two types of traders (expert and novice) have several features in common, we propose a generalization: the Trader agent. This sequencing diagram represents the confrontation of supply and demand for stocks by novice and expert traders via the central market. The latter does not act as a centralized entity but as a meeting place used by traders to interact and realize stocks' exchanges. We use FIPA-ACL (Agent Communication Language) specifications to encode the messages' content. The first message *informs* is sent by the central market and informs traders that the transaction day is open. The *add-Role* message announces the presence of traders. It determines also the role played by the sender: *ExpertInvestor* role or *NoviceInvestor* role. *ExpertTrader* and *NoviceTrader* send a *request* message asking for stock information. *CentralMarket* replies for each message by collecting the needed information. After taking decision, *ExpertTrader* can either give advice or recommend a stock to other *ExpertTraders* and *NoviceTraders* through a *Send-Proposal* message. He communicates also the stock trend to the *CentralMarket* via an *inform* message. The *NoviceTrader* can also give advices to other trader playing *NoviceInvestor* role. Three choices are then possible for traders: (1) if the decision is to hold, trader refuses the proposal, (2) if the decision is to buy and the trader purchases capitals, he accepts buying and he sends a buy order via an *Accept-Proposal* message and (3) if the decision is to sell and the trader owns stocks, he accepts selling and he sends a sell order. We define a market order as a request to trade a specific quantity of a stock at specific price. Every 30 seconds during a trading day, *CentralMarket* executes the fixing by matching sell and buy orders and calculating the market price of the considered stock. Then, a notification (*send* message) is transmitted to the correspondent senders of executed orders.

2.2 Trader making decision

We assume that the trader targets a single goal during a trading day. The goals taken into account by our model are the security of the capital, profitability and speculating and finally liquidity and availability. The objective influences all processes of the model and determines the trader *schedule* (the period during which it remains inactive on our artificial stock market). This schedule ranges from 1step of simulation (which marks an active trader) and 20 steps. If the trader aims to secure his capital, his schedule will be relatively large compared to those who seek opportunities to capitalize on speculating. While the schedule for the trader who opts for liquidity and availability will be regular. The cognitive behavior model of the trader illustrated in figure 3 describes his perceptual, informational and decisional processes. It includes the behavioral attitudes which influence these processes. We notice that this figure represents both expert and novice trader behavior since the rational component includes fundamental and chart analysis. In fact, in our model, the novice trader makes use only of the chart analysis.

2.2.1 Perceptual process

The trader agent is accepted in the market if and only if it plays an expert or novice role and verifies the four following conditions during the simulation: (1) the agent has a wealth not null, (2) the agent leaves the market if he loses its liquidity and does no more stocks in its portfolio, (3) the agent can issue an order to buy only if his liquidity has corresponding to the total amount, so it can issue an order to sell a number of shares only if he has in the corresponding quantity of stocks in its portfolio and (4) there is a *schedule* relative for each agent after which he observes the market.

The agent takes into account the message received if it is filtered through the filter of privacy and / or the filter of confidence. For the privacy filter, if the sender of the message is part of trust network of the receiver, the message is accepted. Otherwise, the message is refused. For the confidence filter, if the acceptance threshold is lower than the information certainty threshold, this information is taken into account. Otherwise, the receiver refuses the message.

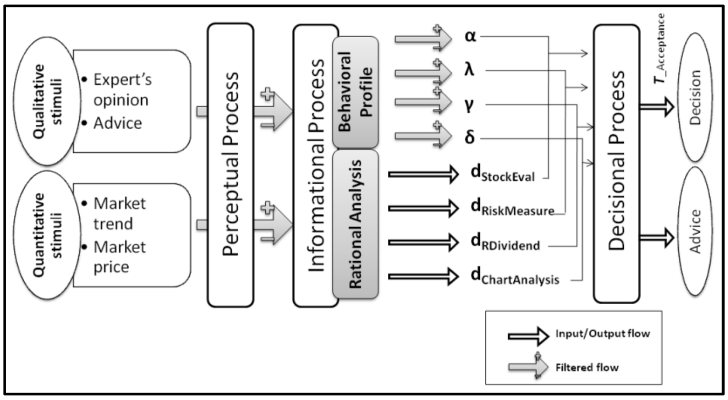

Fig. 3. Trader making decision

2.2.2 Informational process

For our modeling, we adapt four complementary approaches necessary to accomplish rational analysis: (1) stock evaluation, (2) risk measuring, (3) growth rate of dividends and (4) chart analysis. Each analysis provides a numerical signal *d* to buy, to sell or to hold (respectively +1, -1 and 0). We assume that these analyses are used only by ExpertTrader. However, NoviceTrader uses just the chart analysis. The latter agent can not anticipate changes in the stock price only from the chart analysis. He uses so indicators calculated by expert traders. These indicators are also transmitted to CentralMarket agent. The latter agent offers the following actions: (1) launching of the stock market transactions, (2) publication of information related to stocks for traders, (3) matching orders of sale and purchase and execution of transactions via the fixing, (4) updating stock information and (5) calculating the market trend.

Rational analysis

The first analysis is based on the constant growth model (known as Gordon Shapiro model). This model only requires data from one period and an average growth rate which can be found from past financial statements [20].

The second analysis is based on the risk measuring. We used the notion of systematic risk (or market risk), which is indicated by a given coefficient β. This coefficient indicates how the expected return of a stock or portfolio is correlated to the return of the financial market as a whole. It is calculated by the *CentralMarket*.

The third analysis determines the growth rate of dividends. The latter is necessary in order to use the dividend discount model, which assumes that a stock's price is determined by the estimated future dividends, discounted by the excess of internal growth over the firm's estimated dividend growth rate.

The fourth analysis is based on the hypothesis that the past development of a financial asset provides better information about its own future. In our model, we are guided by the Points and Figure Charting (PFC) [7]. This method represents the changes of the stock price and announces the signal of buying or selling.

Behavioral attitudes

We introduce in our model three pairs of behavioral attitudes. For the representation of behavior attitudes, we adopt the generic approach introduced in [4]. This approach is based on the specification of a set of inhibitor and triggering thresholds. In fact, each trader agent receives various kinds of qualitative stimuli (experts' opinion and advice) and quantitative stimuli (market trend and market price). The stimuli affect the trader agent decisions of buying or selling.

- Optimism / pessimism attitudes

In our model, this behavioral component plays a crucial role in determining the estimated rates. The optimistic trader agent, which has a confidence in the outcome, does not react the same way as the pessimistic trader agent. These attitudes affect the rational analysis and more specifically the evaluating performance. Furthermore, in the informational process of our model, optimistic trader agent over-estimates rates while the pessimistic trader agent under estimates them.

- Speculation/caution attitudes

A speculator trader agent decides to conduct a transaction (buy or sell) by accepting the risk of losing in order to gain maximum benefits. Besides, a cautious trader agent proceeds with prudence and prefers to take every detail into account before buying or selling. This difference influences the rational analysis. Indeed, the speculator trader agent decides to buy a stock even if it presents a high rate of risk, something unacceptable by the cautious trader agent. We consider that these attitudes affect also the perceptual process.

- Imitation/leadership attitudes

An imitator trader agent reproduces unconsciously the reaction of his entourage of traders. It follows and is aligned with the overall trend of the market. Whereas, the leader holds the dominant market position and take initiatives to buy or sell stocks. These behavioral attitudes influence the perceptual process which is more extended for the leader than the imitator trader. Indeed, the number of persons composing the confidence network (called TrustNet) of an imitator trader is larger compared to the leader one who has confidence in a few number of traders.

2.2.3 Decisional process

The ExpertTrader agents' decision-making takes place after the four tests relative to: stock evaluation, risk measuring, dividend rate measuring and chart analysis.
Each test gives out respectively a signal to buy, sell or do nothing respectively designed by $d_{StockEval}$, $d_{RiskMeasure}$, $d_{RDividend}$ and $d_{ChartAnalysis}$. The final decision (as shown in figure 3) is calculated as follows:

$$D = \alpha * d\_StockEval + \lambda * d\_RiskMeasure + \gamma * d\_RDividend + \delta * d\_ChartAnalysis.$$

We notice that the parameters α, λ, γ *and* δ are generated randomly under the condition that their sum is equal to 1. Therefore, D ranges from -1 (which indicates buying) to +1 (which indicates selling) and just represents a signal. We note that D will be transformed to an order expect if $| D| \leq$ *ThRunTr*. *ThRunTr* defines a threshold for which the agent runs a transaction following its decision-making. We assume that the *ThRunTr* related to the cautious investor is lower than the one considered by the speculator investor.

2.3 Social networks and interactions

In this section, we discuss the social interconnections in our artificial stock market. We underline the effects of the trader neighborhood on the making decision process and on the emergence of a global behavior. Indeed, behaviors of traders are related to structures in which they fit. The Trader agent is in a direct relationship with other agents. In our simulation, the neighborhood is not physical but it is a neighborly relationship (trust, privacy, etc.). A trader can make and receive advice or opinion of its neighbors. The links between traders are very complex and characterized by two effects, namely the clustering effects and the small word effects [3].

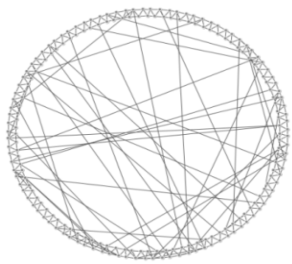

Fig. 4. Watts-Strogatz model of social network in our artificial stock market

We assume that the stock market is represented by a Watts-Strogatz (W-S) model [24] of social network. The W-S model illustrated in figure 4 fits very well on both small-word and clustering characteristics. It provides investors' clusters where information circulates randomly among heterogeneous set of traders. At each time step, investors are grouped into clusters creating neighborhoods of connected agents.

3 Simulation and results

Our simulator is implemented using the MadKit platform [11] using java programming language. For all the experiments, we run the simulation on 25000 steps with one stock traded and 200 investors (divided into 80 expert investors and 120 novice investors). A w-s social network is defined where agents are interconnected with their 4 nearest neighbor and randomly with each possible other agents using a probability of 10%. This results in a one dimensional circle illustrated in figure 4 where traders have 6 contacts on the average. Average length path is 5,8 and cluster coefficient equals to 35,27%. We observe some statistical results which show that many stylized facts of real stock markets are reproduced with our model.

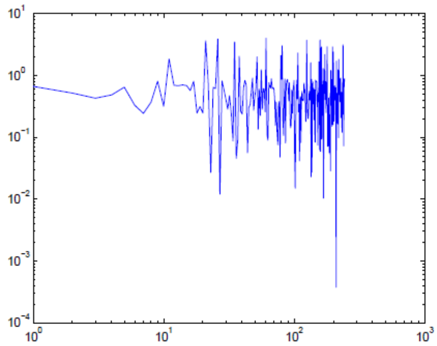

Fig. 5. Scaling of autocorrelations

In order to study autocorrelations in the measure of volatility, we represent the loglog plot of the logarithmic returns $ret(h) = log\ p(h) - log\ p(h-1)$ (Figure 5). The model thereby introduces price volatility correlations which is an element of stylized facts.

In figure 6, we present the fat tails of returns. Figure 6.a presents a normal probability plot of price returns. We are typically concerned about whether the price return is distributed according to a normal distribution, since many of the statistical inference procedures that we use require the assumption of normality of the returns. For comparing, the solid line represents the cumulative distribution of the standard normal distribution *N(0,1).*

Besides, price returns exhibit fatter tails than the standard normal, or Gaussian, distribution and presents a kurtosis equals to 5.52. The leptokurtosis distribution is shown in figure 6.b. This figure presents the price returns distribution compared to a theoretical normal distribution.

Furthermore, financial time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes, and small changes tend to follow small changes. In this case, changes from one step to the next are typically of unpredictable sign. Large perturbations, positive or negative, become part of the information set used to construct the variance forecast of the next period's perturbation. In fact, large shocks of either sign are allowed to persist, and can influence the volatility forecasts for several periods.

(a) (b)

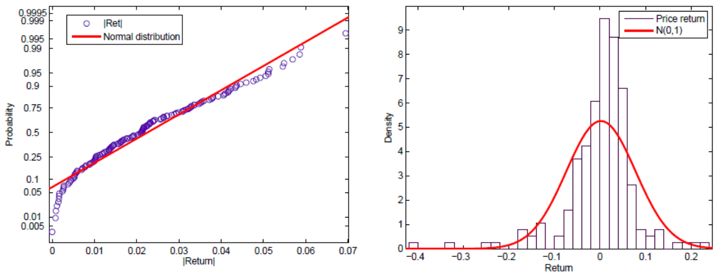

Fig. 6. Fat tails: (a) Normal probability plot of logarithmic returns, (b) Leptokurtosis of the distribution of returns.

We conclude that our behavioral model is able to reproduce some stylized facts observed in real stock market and to assure no predictability of future price developments and an efficient price formation.

4 Conclusion and future works

Our research focuses on the modeling of the stock market trading through modeling the behavior and decision making of investor agent. Our contribution is to consider the stock market as a social organization of autonomous actors with dependents heterogeneous beliefs and different behavioral attitudes. Our model exhibits the observation of some stylized facts (i.e., volatility clustering and fat tail) and assures no predictability of future price developments and an efficient price formation.

Different perspectives can be considered in our work. The first is to focus on the study of others stylized facts such as the Multi-scaling. The second is to explore the memory effect and the uncertainty at various levels in the stock market.

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