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Abstract. In this paper, we introduce a new model of Investor cognitive behavior in stock market. This model describes the behavioral and cognitive attitudes of the Investor at the micro level and explains their effects on his decision making. A theoretical framework is discussed in order to integrate a set of multidisciplinary concepts. A Multi-Agent Based Simulation (MABS) is used to : (1) validate our model, (2) build an artificial stock market: SiSMar and (3) study the emergence of certain phenomena relative to the stock market dynamics at the macro level. The proposed simulator is composed of heterogeneous Investor agents with a behavioral cognitive model, an Intermediary agent and the CentralMarket agent matching buying and selling orders. Our artificial stock market is implemented using distributed artificial intelligence techniques. The resulting simulator is a tool able to numerically simulate financial market operations in a realistic way. Preliminary results show that representing the micro level led us to build the stock market dynamics, and to observe emergent socio-economic phenomena at the macro level.

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

1 Introduction

The complexity of the financial rules governing the stock market and their confrontation with Investors' activities make the explication of observed global behavior very difficult to understand. Empirical and numerical analyses are powerful; nevertheless they still insufficient [10]. We notice that the existing mathematical and statistical models have shown critical limits by failing to explain and to anticipate the extreme perturbation we are living during the last months of 2008.

Previous researches, such as in [13] and [8], are generally based on the hypothesis of rational behavior. However, recently, emerged evidences show that stock markets could not be only studied with a rational paradigm such as in [1] and [17]. In the last decade, we complete the description of theoretical phenomena by many aspects based on the individual's behavior and their interactions. We distinguish an evolution of approaches used to study the stock market: (1) numerical approach during the eighties: [13] and [8], (2) multi-agent based systems during the nineties: [15], [6], [16], [17], [1] and [21] and (3) behavioral multi-agent based systems in recent years: [11] and [10]. This evolution shows that the multi-agent based simulation is a promising approach to study the stock market. An excellent overview of former and significant models in agent-based computational finance is given by [14]. These models range from relatively simple models like the one of [15] to very complicated models like the Santa Fe Artificial stock market [2].

This paper is structured as follows. In the second section, we introduce our integrative theoretical framework. This framework exposes concepts considered in our model. In the third section, we design a new conceptual model of the Investor which is based on rational and cognitive mechanisms. Finally, in the fourth section, we present our simulator named SiSMar: Simulation Stock Market. We expose the experiments led with this simulator in order to observe the impact of behavioral attitudes on the investor decision and the emergence of socio-economic phenomena at the macro level.

2 Integrative theoretical framework

We focus on behavioral finance. It uses social psychology and sociological insights to clarify phenomena. However, we can not pass over the numerical and the economic approaches.

- Behavioral finance

Behavioral finance is the paradigm where financial markets are studied using models that are wider than those based on Von-Neumann Morgenstern expected utility theory and arbitrage assumptions [20]. Psychologists have shown that the real behavior of investors can not be explained only by the basic economic assumptions [12]. The decision of these actors is influenced by behavioral factors such as speculation, pessimism, caution and self control.

- Economic sociology

The goal of economic sociology is to study the social interactions in markets and how social structures are created and are evolved. According to [23],"economic sociology suggests that it is necessary to meet the economic and sociological theories in order to provide better explanations of economic concepts". It considers the social circumstances for economic change, and the effects of these arrangements upon social dissimilarity and well-being [7]. This discipline seeks to understand how the modern economy could be integrated into the social institutions. It involves the micro and macro organizational behavior of investor under risk.

- Cognitive psychology

Cognitive psychology is the study of empirical process of information involved in human behavior. It aims to explore how individuals perceive their environment (neighborhood), how they understand, diagnostic and solve problems. It also intends to analyze how they store information about the location outside or themselves and interpret this information. This discipline examines internal mental processes such as problem solving, perception, short-term memory, long-term memory, habits, and anxiety [18].

- Financial economics

Financial economics determines a set of rules used by investors and managers in decision-making process [22]. This discipline examines the price formation under risk and inspects volatility under the supply and demand mechanism.
A fundamental assumption in financial economics theory is the linear relationship between risk and return. An issue of this assumption is the efficient market hypothesis [5]. This hypothesis assumes that investors act permently in a rational way and attempt to maximize the expected utility of their risk and return decisions.

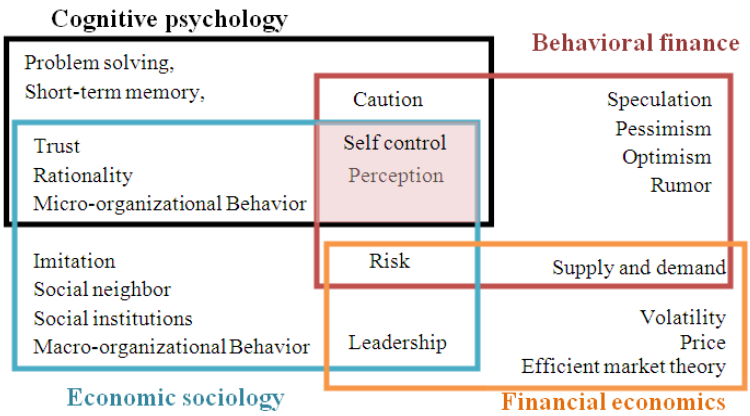


Fig. 1. Integrative theoretical framework of our model

Figure 1 represents concepts and their related domains which constitute our integrative theoretical framework. This framework underlines the multidisciplinary character of certain concepts such as trust, risk and perception.
According to the behavioral finance, we interpret the stock market dynamics as a direct result of the confrontation of the demand for capital by companies and the bid capital from novice and expert investors. In fact, in this paper, we identify mainly three kinds of actors: novice investors, expert investors and market intermediary. In reality, all the transactions happen through an intermediary who manages the supply and the demand and seeks to ensure a balance.

3 Stock market model

We describe now the investor behavior while taking the decision of selling or buying and the interactions between the stock market actors. Our model includes two granularity levels: the micro and the macro level. At the micro level, it describes the cognitive behavior of investors. In addition, it represents actors' interactions. These interactions participate in the emergence and stabilization of socio-economic phenomena observed at the macro level which influence reciprocally behavior and individual interactions. Figure 2 shows the global stock market dynamics integrating micro and macro levels. It specifies at the micro level the five sequential steps for the transaction realization.

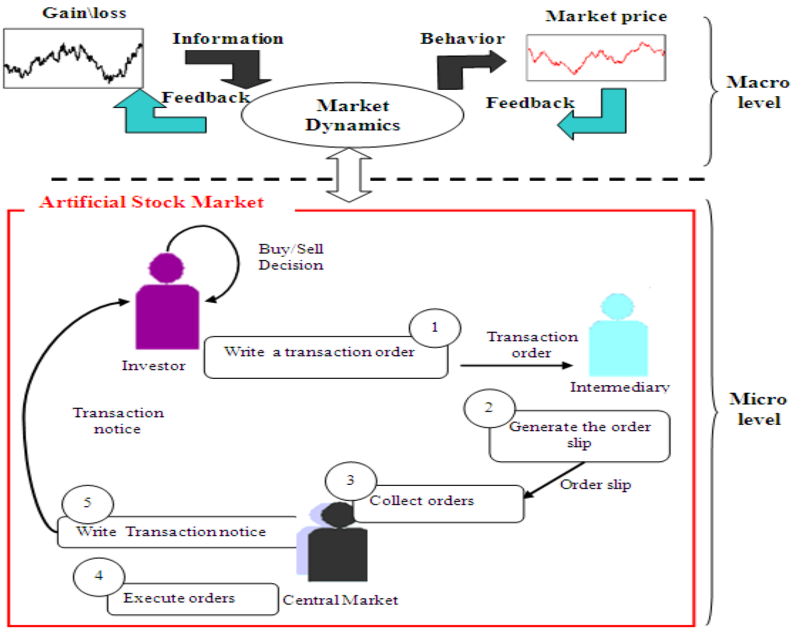


Fig. 2. The micro/macro level dynamics of the stock market

We introduce mainly two hypothesis for the constructing of our model. We assume that the stock market is represented by a social network where information circulates randomly among heterogeneous set of investors. This information concerning stocks and indexes is available permanently for all investors. Their interactions described in figure 2 form the stock price. We neglect the external factors as financial crushes due to crisis, wars and climatic disasters. In addition, we admit that the buying and selling are accomplished immediately and closed out the same day. More explicitly, if an investor gives a purchase order, he must own in advance the capital corresponding to the amount of his purchase. In opposition, if he gives a sell order, he must own in advance the corresponding stocks.

Our artificial stock market is composed of: (1) a set of agents corresponding to the considered three types of actors: ExpertInvestor agents, NoviceInvestor agents and Intermediary agents, (2) a CentralMarket agent responsible of conducting transactions and controlling the dynamics of the stock market. The novice investor acquires a summary knowledge of financial analysis, while expert investor is mainly based on a more complex analysis. The cognitive behavior model of the investor describes his perceptual, informational and decisional processes. It includes the behavioral attitudes and the social profile which influence these processes.

3.1 Rational analysis

The rational analysis is composed of fundamental analysis and chart analysis.

- *Fundamental analysis*
  For our modeling, we adapt the two complementary approaches necessary to accomplish fundamental analysis. The first is the *Stock Evaluation* which 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 [19]. The second approach is *Performance Measuring* which is based on calculating rates of return and risk. In fact, the rate of total return on shares is composed of the rate of overall performance in dividends and the return of capital. 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 agent.

- *Chart analysis*
  Chart analysis is based on the hypothesis that the past development of a financial asset provides better information about its own future. The trend of our artificial stock market is determined by the CentralMarket agent from trends calculated by all expert investors. If the trend is upward, it implies that the stock value should continue to rise. The market presents an uptrend. If investors realize that the following value outside the market price, they notice a sign of rising. Otherwise, it announced a reversal of trend (downtrend) and causes a signal to sell. In our model, we are guided by the Points and Figure Charting (PFC) [4]. This method represents the changes of the stock price.

3.2 Behavioral analysis

We introduce in our model three pairs of behavioral attitudes: *optimism/pessimism, speculation/caution and imitation/leadership*. For the representation of behavior attitudes, we adopt the generic approach introduced in [3]. This approach is based on the specification of a set of inhibitor and triggering thresholds. In fact, each Investor agent receives various kinds of qualitative stimuli (experts' opinion, prediction and advice) and quantitative stimuli (market trend and market price). The stimuli affect the Investor agent decisions. Their effects are weighted according to the Investor agent behavioral profile described through the three remaining pairs of behavioral attitudes. These attitudes play the role of reactive modulators that filter and weight the effect of external stimuli.

- *Optimism/pessimism attitudes*

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

- *Speculation/caution attitudes*

A speculator Investor agent decides to conduct a transaction (buy or sell) by accepting the risk of losing in order to gain maximum benefits. Besides, a cautious Investor 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 Investor agent decides to buy a stock even if it presents a high rate of risk, something unacceptable by the cautious Investor agent. The parameters taken into account in PFC method related to the chart analysis are also influenced by this behavioral component. Besides, we consider that these attitudes affect the perceptual process. In fact, a speculator investor presents a lower threshold of acceptance information than a cautious investor.

- *Imitation/leadership attitudes*

An imitator Investor agent reproduces unconsciously the reaction of his entourage of investors. 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 investor. Indeed, the number of persons composing the confidence network (called TrustNet) of an imitator investor is larger compared to the leader one who has confidence in a few number of investors.

4 Simulation and experimental results

4.1 SiSMar: The artificial stock market

SiSMar (Simulation Stock Market) is an artificial stock market composed of a set of Investor agents having diversified behavioral attitudes and social profiles. The purpose of this simulation is to understand the influence of psychological character of an investor and its neighborhood on its decision-making and their impact on the market in terms of price fluctuations. Our simulator is implemented using the MadKit platform [9] and is written in Java.

The Investor 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.). An investor can make and receive advice or opinion of its neighbors. However, the agent takes into account the message received if it is filtered through the filter of privacy and / or the filter of confidence. On 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. On 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 and ignores it. We assume that the cardinal of TrustNet is less than or equal to six investors for novices and it does not exceed two for experts. This network is dynamic, since if the chart analysis of the agent does not coincide with the advice of a member of his TrustNet, the information is ignored and the investor eliminates the sender of this message and randomly chooses another one. At each simulation step, every Investor agent may behave in several ways, depending on his state. He may be inactive if the number of simulation steps designated by t is not a multiple of its periodicity;

Once active, Investor agents interact on the market. The ExpertInvestor agents' decision-making takes place after processing four tests relative to: stock evaluation, risk measuring, dividend rate measuring and chart analysis. Each test gives out a signal to buy, sell or do nothing respectively designed by $d_{StockEval}$, $d_{RiskMeasure}$, $d_{RDividend}$ and $d_{ChartAnalysis}$. The final decision is calculated as follows:

$$\mathbf{D} = \alpha * \mathbf{d}_{StockEval} + \gamma * \mathbf{d}_{RiskMeasure} + \lambda * \mathbf{d}_{RDividend} + \delta * \mathbf{d}_{ChartAnalysis}$$

With: $\alpha + \gamma + \lambda + \delta = 1$.

The NoviceInvestor agent anticipates changes of the stock price using only chart analysis and filtered information diffused by its neighborhood.

4.2 The market price volatility evolution

The purpose of this experiment is to observe the magnitude of changes in stock prices. Figure 3 represents the evolution of four stocks in a bull market and its evolution when the trend is downward. On figure 3.(a), we notice that the upward movements are longer than those of downward. This reflects a resistance to downtrend pressure on the bull market. In addition, changes in the prices of the four studied stocks are very considerable which shows that a large number of transactions were executed. Contrarily, on figure 3.(b), we observe some positive stock price fluctuations however dominated by a global downtrend. We can conclude that there is resistance to the increase in the bear market. These two results are in line with what happens in reality on a stock market and coincide with the principles of Dow Theory. In this experiment, we observe the change in stock price in a market where the trend is not determined from the outset. We assume that Investors' experts, as the market leaders, calculate at every step of simulation the tendency of stocks and send it to the Central Market. The last one determines the overall trend.

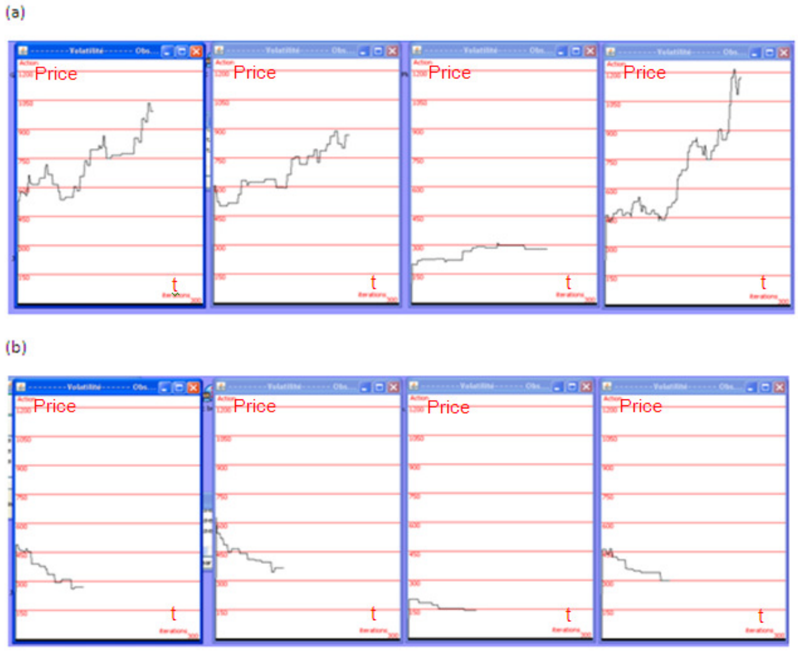
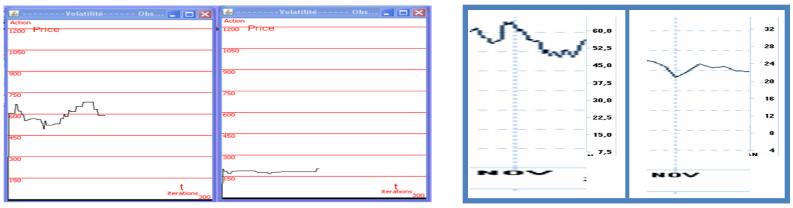


Fig. 3. Analysis of market trend of four stocks: (a) uptrend market, (b) downtrend market.

We take the example of these two stocks[1] presented in figure 4. The table 1 resumes the characteristics taken into consideration in this experiment, with a population composed of 50 ExpertInvestor agents and 80 NoviceInvestor agents.

We observe a very significant volatility of the first stock figure 4.(a) compared with that in the second figure 4.(b) despite that the price of the second is much lower than the first and they all possess both an upward trend.

[1] We notice that data relative to these two real stocks, Peugeot and Air-France, are extracted from EuroNext Paris (november 2007) and used to calibrate the parameters of our simulator.



(a) (b) (a*) (b*)

Fig. 4. Comparative of the stock volatility: (a) Peugeot volatility overall SiSMar, (b) Air-France volatility overall SiSMar, (a*) Peugeot volatility overall EuroNext Paris (November 2007), (b*) Air-France volatility overall EuroNext Paris (November 2007).

We explain this fact by the coefficient β which influences the rate of risk and it is considered by the behavioral profile of our Investor agents. More than β is near to 1, more the stock is risky. This risk is visible by the measure of volatility. In addition, the annual dividend offered by a stock improves the number of transactions of this stock. This fact increases his volatility. We notice also that the volatility of these two stocks overall SiSMar is very close to the values extracted from reality (figure 4.(a^*),(b^*)). What we are emphasizing here is that it is possible to reproduce realistic market evolutions using the SiSMar behavioral model.

Table 1. The characteristics considered of two stocks: Peugeot and Air-France

Name	Peugeot	Air-France
Acquisition Price	60.7	20.2
Annual dividend	3.1	0.9
Trend	1	1
Β	0.6	0.2

5 Conclusion and future works

In this paper, we introduced a new model of stock market dynamics. Our research focuses on the modeling of the stock market and particularly modeling the behavior and decision making of two types of Investors: novice and expert Investor. Our contribution is to consider the stock market as a social organization of autonomous actors with dependents heterogeneous beliefs and different behavioral attitudes. Different perspectives can be considered in our work. The first is to refine the model and enrich its implementation with including new cognitive concepts at the micro level. Learning techniques and fuzzy logic can be used respectively to explore the memory effect and the uncertainty at various levels in the stock market. Whereas, the perceptual process may include components which are based on fuzzy sets such as threshold triggers and inhibitor sets.

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