ADAPTIVE AGENTS MODELING AND SIMULATION IN ARTIFICIAL FINANCIAL MARKET

Dalel Kanzari

Department of Computer Science
Sousse University
RIADI-ENSI laboratory, Tunis
Sousse, TUNISIA
kndalel@yahoo.fr

Yosra Ben Said

Department of Management
Sfax University
E.A.S research unit, Mahdia
Sfax, TUNISIA
yosra.bensaid@yahoo.fr

ABSTRACT

Agent-based artificial financial market generally models the agents' interactions and their impact on the price dynamics and the market stability. We propose to conceive and simulate a new approach of traders' models that adapt their behaviors to the market conditions (stability V.S instability) variation, to prove the dynamic of the price security formation in the financial market. We consider three kind of traders: The rational-adaptive investors who are more fundamentalists during stable regime but dynamically mutate to behavioral and mimetic during crisis regime. The noise traders who are irrationals; they switch between overconfident and loss adverse behaviors; Mimetic traders who adopt a mimetic behavior and follow the most dominant decision in the market. Our experimental results show that the dynamic behavior of the rational-adaptive investors, that become irrational in instability periods, is a relevant determinant of the crisis periods.

Keywords: Agent-based Models, Artificial Stock Markets, rationality, noise traders, Mimetic.

1 INTRODUCTION

Since the early twentieth century, fundamental and empirical researches on the functioning of financial markets have increased. These researches are often interdisciplinary. Indeed, financial markets have several aspects: financial (the study of economic issues), mathematics (study of price series properties) and human (study of the psychology of economic actors). Yet none of these disciplines today happens to offer a complete theory able to overcome the complexity of the markets. Computational finance, a crossroads of several research fields (computer science, game theory and finance), emerged to overcome the limitations of previous work. This new discipline reproduces the market functioning in artificial worlds, perfectly controlled. These worlds are reproduced through parallel executive computer systems; called Multi-Agent Systems (MAS). Hoffmann et al. (2007); Kouwenberg and Zwinkels (2015); Rekik et al. (2014); Levitin and Wachter (2012); Simone et al. (2010) and Stefan and Atman (2017) adopted the MAS models in an artificial market to explain the functioning of financial markets and anomalies in these markets. Hoffmann et al. (2007) introduced the bounded rational concept, the prospect theory of Kahneman and Tversky (1979), the conformity behavior concept and theories on different social network.

To explain the excess volatility in the stock market, Kouwenberg and Zwinkels (2015) studied a mimetic behavior among two types of traders: fundamentalists and noise traders. Rekik et al. (2014) built a multi-agent model in an artificial stock market composed of fundamentalists, non-fundamentalists and loss aversion investors. Levitin and Wachter (2012) showed that a multi agents model with chartists and fundamentalists endogenously produces boom and burst cycles. Their result shows that interaction between agents can explain the bubbles in the absence of underlying fundamental news. Benhammada et al. (2017) considered four types of investors: fundamentalists who make a decisions based on the fundamental value of assets; hybrids who are initially fundamentalists, but switch to a speculative strategy when they detect an uptrend in prices; noise traders who don't have sufficient information to take rational decisions, and finally mimetic traders who imitate the decisions of their mentors on the interactions network.

Said et al. (2018) propose a conceptual model of financial decision-making representing the stock market dynamics during the crisis period. In their model, institutional investors are rational whereas individual investors are noise traders, not fully rational; the arbitrage is risky and limited. They demonstrate that overconfidence and loss aversion are relevant to explain the formation and bursting of bubbles. Mimetic behavior amplifies disturbances in the financial market and limits arbitrage.

In our work, we use models of multi-agent systems in an artificial financial market to reflect the complexity of the financial market system (Hoffmann et al. 2007; Kouwenberg and Zwinkels 2015; Rekik et al. 2014) the interactions between agents themselves and between agents and their environment. We propose a new approach of heterogeneous traders' models to prove the dynamic of security's price formation in the financial market. Traders adapt their behaviors to the market regimes (stability V.S instability). We consider three kind of traders: The rational-adaptive investors who are more fundamentalists during stable regime but dynamically mutate to behavioral and mimetic during crisis regime. The noise traders who don't have sufficient information to take rational decisions; they switch between overconfident and loss adverse behaviors; Mimetic traders who adopt a mimetic behavior and follow the most dominant decision in the market. To test the model we perform a series of experiments, and we analyze their results. This paper is organized as follows. The section 2 presents our proposed investors agent-based models. We perform a series of experiments and we discuss the results in section 3. Section 4 concludes and outlines open research directions.

2 THE PROPOSED INVESTORS MODELS

In our model, we consider three types of investor: rational (fundamentalist), noise traders and mimetic. Three types of decisions are possible: rational decision (DR), behavioral decision (DBh) and mimetic decision (DM).

We propose to study the dynamics of asset prices in the financial market for its two regimes: the period of stability and the crisis period (instability) (Hamilton 1989). In times of crisis, we have two phases: Phase 1 of the bubble formation (upward trend in the securities' prices) and phase 2 of the bubble bursting (prices collapse).

2.1 Agents models

The market in our model is populated by three types of agents: rational-adaptive investors, noise traders and mimetic traders. All investors are only interested in short time capital earnings and not motivated by long term rent income (Kouwenberg and Zwinkels 2015). The rational-adaptive investors are fundamentalists during stable regime but behavioral or mimetic during crisis regime. The noise traders are irrationals, they can be overconfident or loss adverse with different degrees; the overconfident individuals overestimate their information and their capacities. The loss adverse people tends to feel the loss more than the earnings for the same scale the mimetic investors are influenced by the decision of their peers. The latter may hold private information about the return on the investment and their decisions reveal this information; money managers can imitate others when the incentives are based on yield reference and the investors can have an intrinsic preference for conformity.

For determining the expect return $E_t\ (R_{t+1})$, each type of investors has its own rule. The fundamentalist rule or rational decision (RD), showed in equation (1) is based on the expectation of the mean reversion of the market price towards the long term fundamental value (Kouwenberg and Zwinkels 2015).

$$RD = E_t\ (R_{t+1}) = \alpha(P_t - F_t) \tag{1}$$

F_t : is the log real fundamental price of the security at time t;

P_t : is the log security price at time t.

$\boldsymbol{\alpha} < 0$: is the speed of mean reversion expected by rational investors.

The noise traders trader investors suppose a positive autocorrelation in returns. Their rule is described by the equation (2):

$$E_t(R_{t+1}) = \beta(\textstyle\sum_I^L R_{t-I+1}) \tag{2}$$

β (>0) is the extrapolation parameter, L (>0) is a positive integer that indicates the number of lags. For experiments, we choose L= 6 periods.

The attitude of each noise trader influences the decision of buying or selling. Their definitive rule or behavioral decision (BD) is given by the equation (3) (Said et al. 2018):

$$\mathrm{BD}= \mathrm{E_t(R_{t+1})} = \beta\big(\textstyle\sum_I^L \mathrm{R_{t-I+1}}\big) * \mathrm{B_j} \tag{3}$$

$\mathrm{B_j}$: is the bias of each investor j. If $0 < \mathrm{B_j} < 1$, then investor j is loss adverse else if $\mathrm{B_j} > 1$, then investor j is overconfident.

The rational-adaptive investors and the noise traders take a decision of buying and selling according to the sign of the expected return. So if $\mathrm{E_t(R_{t+1})} > 0$ then investors buy the asset, else the investors sell the asset.

The mimetic investor observes the investment behavior of the others investors and evaluates whether there are more selling or more buying agents and then imitates the dominant behavior. The Mimetic rule or mimetic decision depend on the ratio of the equation (4) (Said et al. (2018))

$$\mathrm{MD} = \mathrm{ratio} = \frac{\text{selling advice}}{\text{buying advice}} \tag{4}$$

If $\mathrm{ratio} > 1$, then the mimetic investors sell the asset else the mimetic investors buy the asset.

The rational-adaptive trader adapts his decision's strategy to the market regime; he take a rational decision (RD) when the market is stable (Ft=Pt) and tends toward a behavioral or mimetic decisions when the market is instable.

The rational-adaptive decision is the weighted average of the three types of decisions. His definitive rule or rational-adaptive decision (RaD) is given by this proposed equation (5):

$$\mathrm{RaD} = \alpha\,\mathrm{RD} + \beta\,\mathrm{BD} + \gamma\,\mathrm{MD} \tag{5}$$

- α, β and γ: Represent human behaviors which are rationality, overconfidence/loss-adverse and mimetic characters.

We assume that:

- $\alpha + \beta + \gamma = 1$
- $d = \left|\frac{P_t - F_t}{F_t}\right|$: The absolute difference between the fundamental value F_t and the market priceP_t.
- $\alpha = \frac{1}{(1+d)}$: the rational factor
- β : the behavioral factor, it depends on the d and α variation :
- $\beta = \frac{1}{4}\left(\frac{d}{1+d}\right)$ for $\alpha = \frac{1}{1+d} \in\ ]0\ \ 0.5[$
- $\beta = \frac{3}{4}\left(\frac{d}{1+d}\right)$ for ($\alpha \in\ ]0.5\ \ 1[$)
- $\beta = \frac{d}{2(1+d)}$ for ($\alpha = 0.5$)
- γ : the mimetic factor, it relies also on d and α variation :
- $\gamma = \frac{3}{4}\left(\frac{d}{1+d}\right)$ for $\left(\alpha = \frac{1}{1+d}\right) \in\ ]0\ \ 0.5[$
- $\gamma = \frac{1}{4}\left(\frac{d}{1+d}\right)$ for $\left(\alpha = \frac{1}{1+d}\right) \in\ ]0.5\ \ 1[$
- $\gamma = \frac{d}{2(1+d)}$ for $\left(\alpha = \frac{1}{1+d}\right) = 0.5$

Three cases are presented:

Case 1: $\alpha \in\ ]1\ \ 0.5[$ and then $\alpha > \beta > \gamma$; the agent is more rational than noise trader and mimetic and so the decision (RD) dominates.

Case 2: $\alpha = 0.5$ then $\beta = \gamma$; the agent is yet more rational but influenced by the behavioral and the mimetic decision.

Case 3: $\alpha \in\ ]0\ \ 0.5[$ and then $\alpha < \beta < \gamma$; the agent's final decision is more affected by the mimetic and the behavioral decision.

2.2 Agent-based artificial market rules:

The investors' decisions about buying or selling assets are affected by quantitative market stimuli that are the expected past returns, the fundamental values F_t and the past prices of an asset.

The investors don't have any budget constraints but can only buy or sell one security asset during a period. That is the market security (portfolio composed of all the securities of the market).

At the end of each period, the price of the security is recalculated. It depends on supply and demand in the market during the previous period. The price impact function is given by the equation 6:

$$P_{t+1} = P_t + \partial \left(D(P_t) - S(P_t)\right) \tag{6}$$

- $\partial \leq 0.5$
- $D(P_t)$: The security demand at price P_t over period t.
- $S(P_t)$: The security supply at price P_t over period t.

The equation (6) captures the basic intuition that excess demand raises the price, while excess supply lowers the price. This pricing mechanism is computationally very fast, while the price changes are very sensitive to the choice of the liquidity parameter ∂. We suppose that the parameter delta is variable between 0 and 0.5 for a conventional price's variation close to reality.

The dynamic exchanges process agree the following protocol:

1. The incoming of different new stimuli: the advice, the fundamental values and the past stock prices, to the artificial market for the market assets.
2. Quantitative stimuli affect the agent's analysis and so the decision of buying or selling assets.
3. The final decision can be a buy or a sell or do nothing.
4. The noise traders generate a BD decision (equation 3), rational-adaptive investors make their combined weighting decision RaD (equation 5) and the mimetic agents take the predominant decision MD (equation 4).
5. Investors simultaneously submit their sell or buy orders.

3 EXPERIMENTS AND DISCUSSIONS

3.1 Simulation and experiments

An experimental design is performed to show the feasibility and utility of the proposed model. We simulate the investors' behavior during different regimes of the financial market as well as the spread effect on the others behaviors. We use multi-intelligent agents systems by means of the open-source software program, NetLogo version 5.0.5 (Tisue and Wilensky 2004)

The Figure 1 describes the artificial stock market simulator. The agents in blue represent the mimetic traders, those in green represent the behavioral ones and those in purple represent the adaptive-rational agents. The red area is the buying area and the blue is the selling area.

The experimentations focus on the dynamic interactions between rational, noise and mimetic traders; the later take advice of selling or buying from the first two and tend to imitate their behavior.

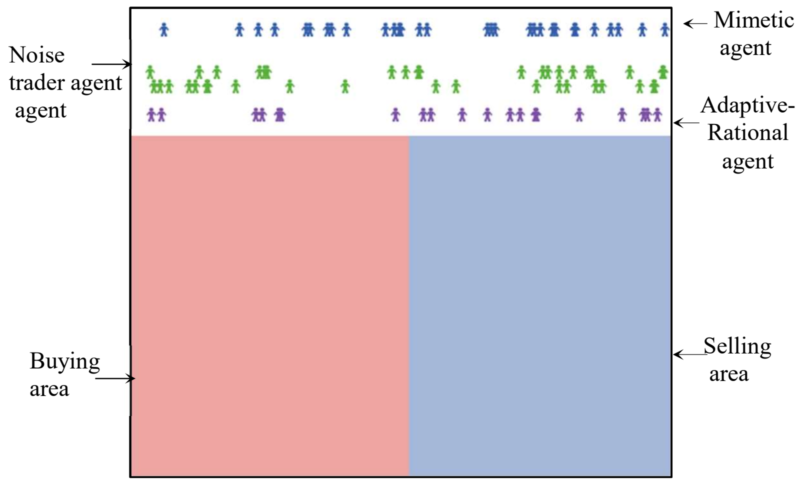

Figure 1: Artificial stock market simulator

Table 1 describes four experiments with different number of traders; in Exp.1: the rational-adaptive are dominant; in Exp.2 the overconfident traders are dominant; in Exp.3 the loss-adverse are dominant and in Exp. 4 the mimetic are dominant. Each experiment has three market's phases: stability regime ($P_t \cong F_t$), instability regime with a market uptrend (boom: $P_t \gg F_t$) and instability regime with a market downtrend (burst: $P_T \ll F_t$). Our aim is to find the type of investor that is responsible of the price dynamic of market assets, to prove that our proposed model give realistic price dynamics and to show that our rational-adaptive model can mitigate the financial market crisis.

3.2 Results and discussions

Table 2 summarizes our experiments' results and show how the rational investor adapts his final decision to the market conditions. So, as presented before, the rational investor's decision is based on a weighted average function (equation (5)) of three types of decisions: a rational, a behavioral and a mimetic decision and it depends on the phases (stability regime, Boom regime, and Burst regime). Also, we show that the market composition, such as the traders proportions, can affect the rational investor's decision and consequently the asset price formation. We discuss later the results for each phase.

Table 1: Experimental design

Phases	**parameters**		**Exp1**	**Exp2**	**Exp3**	**Exp4**
Stability regime	General parameters of Market	Number of periods	700	700	700	700
		Number of traders	60	60	60	60
		Open price (Pt)	252	252	252	252
		Fundamental value (Ft)	250	250	250	250
		Past returns (Rt-1)	-0.09; 0.1; 0.19;1.2; 0.28; 0.33			
	Proportions of traders	Rational-adaptive investor	1/2	1/6	1/6	1/6
		overconfident	1/6	1/2	1/6	1/6
		Loss adverse	1/6	1/6	1/2	1/6
		mimetic	1/6	1/6		1/2
Instability regime (Boom)	General parameters of Market	Number of periods	700	700	700	700
		Number of traders	60	60	60	60
		Open price (Pt)	185	185	185	185
		Fundamental value (Ft)	150	150	150	150
		Past returns (Rt-1)	0.3; 0.4; 0.5 ;0.6; 0.65; 0.7			
	Proportions of traders	Rational-adaptive investor	1/2	1/6	1/6	1/6
		overconfident	1/6	1/2	1/6	1/6
		Loss adverse	1/6	1/6	1/2	1/6
		mimetic	1/6	1/6	1/6	1/2
Instability regime (burst)	General parameters of Market	Number of periods	700	700	700	700
		Number of traders	60	60	60	60
		Open price (Pt)	150	150	150	150
		Fundamental value (Ft)	185	185	185	185
		Past returns (Rt-1)	-0.3; -0.4; -0.5; -0.6; -0.7;-0.75			
	Proportions of traders	Rational-adaptive investor	1/2	1/6	1/6	1/6
		overconfident	1/6	1/2	1/6	1/6
		Loss adverse	1/6	1/6	1/2	1/6
		mimetic	1/6	1/6	1/6	1/2

Table 2: Experiments' results

Phases	**Experiments**	$\overline{\alpha}$	$\overline{\beta}$	$\overline{\Upsilon}$	**Number of buying orders**	**Number of selling orders**
Stability regime	Exp 1	0.867	0.099	0.033	244	808
	Exp 2	0.860	0.104	0.034	244	864
	Exp 3	0.855	0.108	0.036	244	908
	Exp 4	0.855	0.108	0.036	244	912
Instability regime (Boom)	Exp 1	0.598	0.236	0.164	1102	149
	Exp 2	0.597	0.235	0.167	1113	149
	Exp 3	0.594	0.234	0.170	1129	149
	Exp 4	0.595	0.234	0.169	1126	149
Instability regime (Burst)	Exp.1	0.671	0.246	0.081	184	906
	Exp. 2	0.668	0.248	0.083	184	930
	Exp. 3	0.665	0.251	0.084	184	958
	Exp. 4	0.664	0.252	0.084	184	966

Stability regime. The rational-adaptive trader has a dominant rational decision (α = 0.867). Its decision is less rational when the market is dominated by noise traders or mimetic ones (see table 2). The price trend is the same for the four experiments (Figure 2). The price tend to fall because of Pt < Ft. The number of selling orders differs between the experiments; it is more important for exp.S3 and exp.S4 where the loss adverse traders and the mimetic ones are dominant. In figure 4 (Exp. 1), the rational-adaptive traders give purchase orders to rebalance the market. When the rational-adaptive traders are dominant, they prevent the deviation of prices from the fundamental value and the market tend to the equilibrium. When the loss adverse and mimetic traders are dominant, there is selling pressure; the price tends to collapse and move away from the fundamental value. The market is out of balance.

Instability regime: Boom phase. In Exp.1, the decision of the rational-adaptive agent is shared between a rational part ($\alpha = 0.598$), a behavioral part (β =0.236) and a mimetic one ($\gamma = 0.162$). When prices increase and deviate from fundamental value, the rational-adaptive agent abandons his rational strategy in favor of a behavioral and mimetic decision. They don't prevent the deviation of prices from the fundamental value. The security's price uptrend can be explained by the behavior of the rational-adaptive agent (Fig.3. Exp. 1).

For the four experiments, the rational factor (α) varies with the composition of the market. It is weaker when the market is dominated by loss adverse traders (see table 2. Exp. 4). The price tend to increase rapidly (see Figure 3). The number of buy orders are very high compared to the sell ones. It takes the highest value when the market is dominated by the less adverse traders (Exp. 3), then comes the exp. 4 when the mimetic traders dominate.

Instability regime: Burst phase. The decision of the rational-adaptive agent is shared between a rational part ($\alpha = 0.671$), a behavioral part (β =0.245) and a mimetic one ($\gamma = 0.081$). When prices decrease and deviate from fundamental value, the rational-adaptive agent abandons his rational strategy in favor of a behavioral and mimetic decision. They don't prevent the deviation of prices from the fundamental. The security's price downtrend can be explained by the behavior of the rational-adaptive agent (Fig.4. Exp. 1)

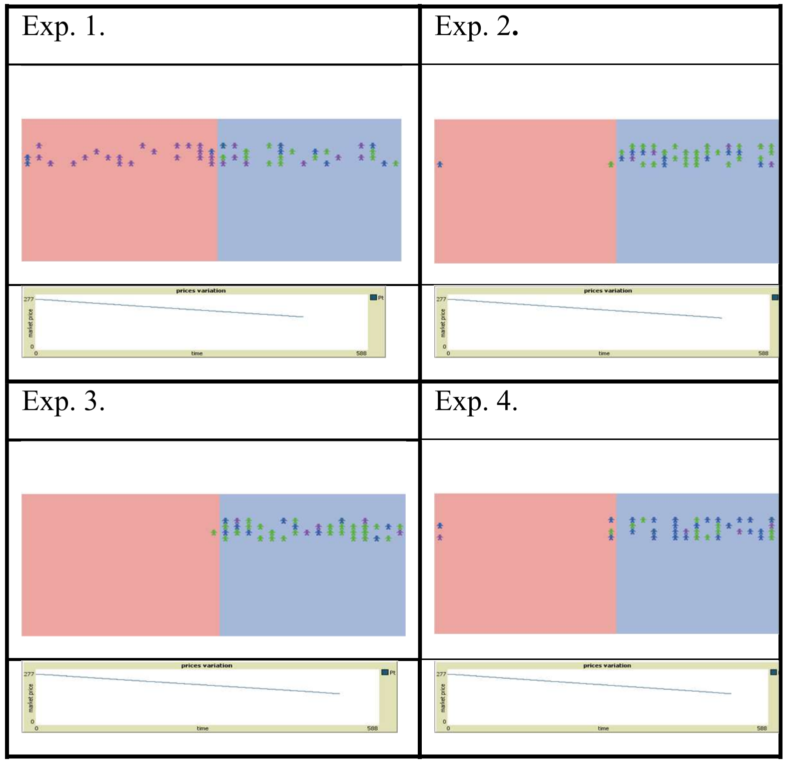

Figure 2: The stability regime

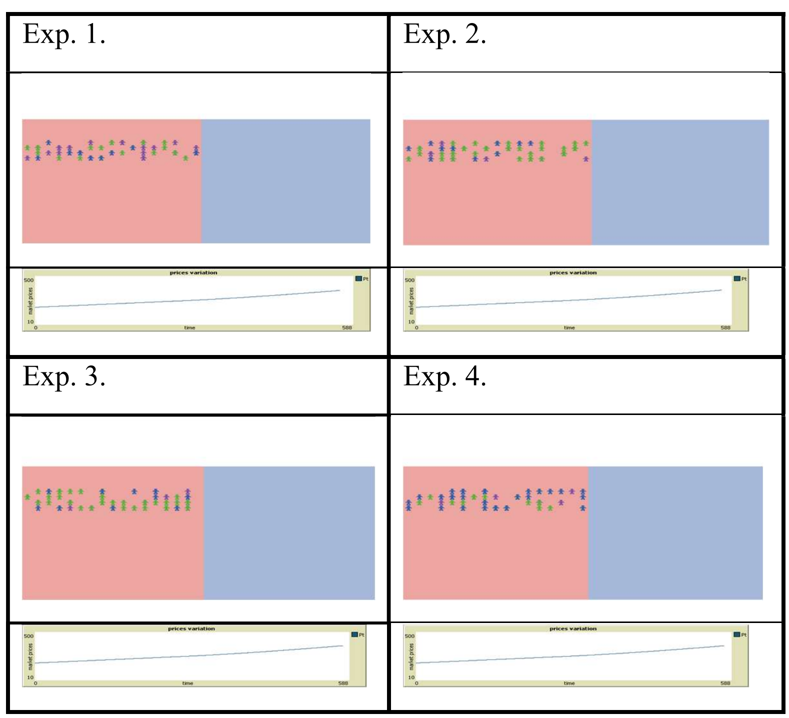

Figure 3: Instability regime: Boom phase

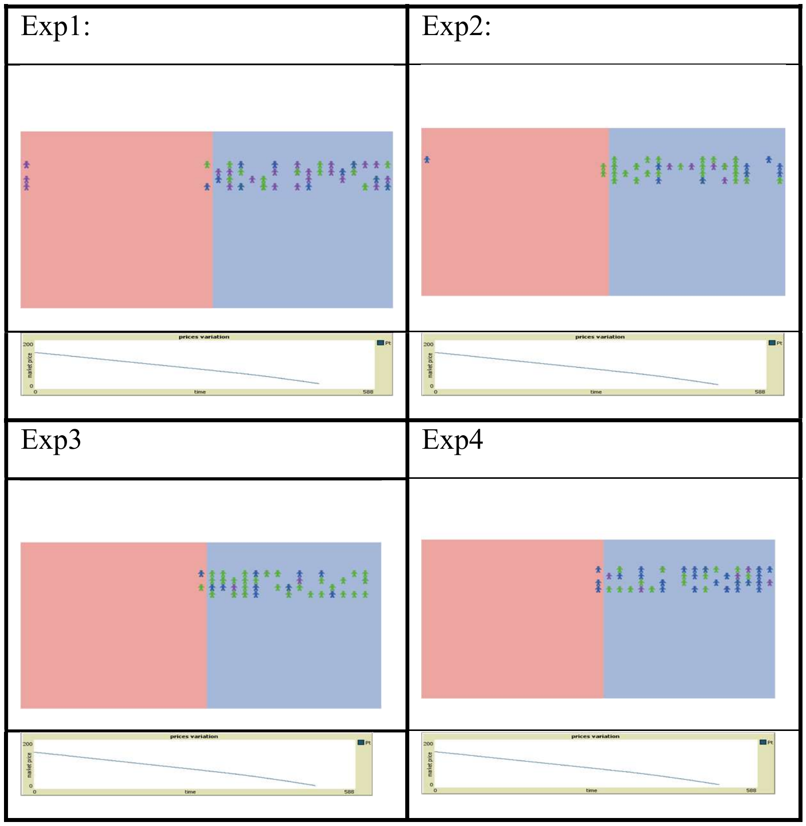

Figure 4: Instability regime: Burst phase

For the four experiments, the rational factor (α) varies with the composition of the market. It is weaker when the market is dominated by mimetic traders (see table 2. Burst phase. Exp. 4).The price tend to decrease rapidly (see Figure 4). The number of sell orders are very high compared to the buy ones. It takes the highest value when the market is dominate by the mimetic traders (Exp. 4), then comes the exp. 3 when the loss adverse traders dominate.

Our experimental results show that the dynamic behavior of the rational-adaptive investors, that become irrational in instability periods, is a relevant determinant of the crisis periods. Besides the relevance of the adaptive behavior of rational investors, we find that loss adverse and mimetic traders have the relevant role in the formation and burst of bubble in crisis period.

4 CONCLUSION

Our work uses models of multi-agent systems in an artificial financial market to reflect the complexity of the financial market system; the dynamic interactions between agents and their environment and its effect on the individual decision-making process of each agent. We propose a new approach of heterogeneous traders' models to prove the dynamic of security's price formation in the financial market. Traders adapt their behaviors to the market regimes (stability V.S instability). We consider three kind of traders: The rational-adaptive investors who are more fundamentalists during stable regime but dynamically mutate to behavioral and mimetic during crisis regime. The noise traders who don't have sufficient information to take rational decisions; they switch between overconfident and loss adverse behaviors; Mimetic traders who adopt a mimetic behavior and follow the most dominant decision in the market

To test the model, we conducted a series of experiments and also, we tested theoretical assumptions which consider mimetic traders as the first explanation of the phenomena of speculative bubble. Experiments have shown that the rational investor have a dynamic decision which fit to the market regime. In the instability regime, the rational trader abandons his rational strategy toward a noise and mimetic ones. Our results prove that the dynamic behavior of the rational-adaptive investors, that become irrational in instability periods, is a relevant determinant of the crisis periods.

Also, results of experiments support theoretical assumptions concerning the important role of mimetic behavior and noise traders as an explanation of excess volatility and bubbles formation. In fact, when market is populated by a majority of mimetic traders or loss adverse traders, imbalance in the market is more pronounced.

We believe that our model is feasible, useful and relevant. In future research, we will ameliorate the model; the fundamental value (Ft) varies over time; the experiments will done with real data; we are interested in the relations between the factors α, β, ϒ and the dynamics of the stock market.

REFERENCES

Benhammada S., Amblard, F. and Chikhi, S. 2017. "An Artificial Stock Market with Interaction Network and Mimetic Agents". *9th International Conference on Agents and Artificial Intelligence (ICAART 2017)*, Porto, Portugal. *Proceedings of the 9th International Conference on Agents and Artificial Intelligence* - Volume 2: ICAART, 2, pp. 390-397.

Demyanyk , Y. and Hemert, O.V. 2011. "Understanding the Subprime Mortgage Crisis". *Review of Financial Studies* vol. 24 (6), pp. 1848-1880.

Hoffmann, A. O. I., WJager, W. & von Eije, J.H. 2007. "Social Simulation of Stock Markets: Taking it to the Next Level". *Journal of Artificial Societies and Social Simulation* vol. 10, no. 2. http://jasss.soc.surrey.ac.uk/10/2/7.html.

Hoffmann, A, Post, T. & Pennings, J. 2013. "Individual investor perceptions and behavior during the financial crisis". *Journal of Banking & Finance* vol. 37 (1), pp. 60-74.

Kouwenberg R. and Zwinkels RCJ. 2015. "Endogenous Price Bubbles in a Multi-Agent System of the Housing Market". *PLoS ONE* 10(6): e0129070. https://doi.org/10.1371/journal.pone.0129070.

Levitin, A. and Wachter, S. 2012. "Explaining the housing bubble". *Georgetown Law Journal* vol. 100, pp. 1177-1258.

Rekik, Y., Hachicha. W. and Boujelbene, Y. 2014. "Agent-based Modeling and Investors' Behavior Explanation of Asset". *Procedia Economics and Finance* vol. 13, pp. 30 – 46.

Said, Y., Kanzari, D. & Bezzine, M. 2018. "A Behavioral and Rational Investor Modeling to Explain Subprime Crisis: Multi Agent Systems Simulation in Artificial Financial Markets". In book: *Financial Decision Aid Using Multiple Criteria*, Springer international publishing. https://doi.org/10.1007/978-3-319-68876-3_6.

Tisue, S., and Wilensky, U. 2004. "NetLogo: Design and implementation of a multi-agent modeling environment". *Proceedings of the Agent 2004 Conference on Social Dynamics: Interaction, Reflexivity and Emergence*, Chicago, IL.

Stefana, F.M., and Atman, A.P.F. 2017. "Asymmetric return rates and wealth distribution influenced by the introduction of technical analysis into a behavioral agent based model". https://arxiv.org/abs/1711.08282.

AUTHOR BIOGRAPHIES

DALEL KANZARI is an assistant Professor in the Higher Institute of Applied Sciences and Technology of Sousse at Sousse University. She holds a Ph.D. in Computer Science from University of Manar (Tunisia), her research interests include the behavioral intelligent agent, machine learning and data science. Her email address is kndalel@yahoo.fr.

YOSRA BEN SAID is an assistant Professor in the faculty of economics sciences and management at Sfax University. She holds a Ph.D. in Finance from University of Manar (Tunisia), her research interests include behavioral finance, dynamic of market prices and Islamic finance. Her email address is yosra.bensaid@yahoo.fr.