# Market dynamics and agents behaviors: a computational approach

Julien Derveeuw

LIFL

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Julien Derveeuw[1]

Laboratoire d'Informatique Fondamentale de Lille - UMR USTL/CNRS 8022
Université des Sciences et Technologies de Lille
Bâtiment M3, Bureau 14a
59655 Villeneuve d'Ascq Cédex
julien.derveeuw@lifl.fr and http://www.lifl.fr/~derveeuw

**Summary.** We explore market dynamics generated by the *Santa-Fe Artificial Stock Market* model. It allows to study how agents adapt themselves to a market dynamic without knowing its generation process. It was shown by Arthur and LeBaron, with the help of computer experiments, that agents in bounded rationality can make a rational global behavior emerge in this context. In the original model, agents do not ground their decision on an economic logic. Hence, we modify indicators used by agents to watch the market to give them more economic rationality. This leads us to divide agents in two groups: fundamentalists agents, who watch the market with classic economic indicators and speculator agents, who watch the market with technical indicators. This split allows us to study the influence of individual agents behaviors on global price dynamics. In this article, we show with the help of computational simulations that these two types of agents can generate classical market dynamics as well as perturbed ones (bubbles and kraches).

## 1 Introduction

Market simulations with the help of computer agents has become in the last few years a growing field of interest under the impulsion of the *Santa-Fe Institute* for example. These simulations allow to predict market evolutions, to validate theoritical hypotheses or to test models in perfectly controlled virtual worlds (Johnson, Lamper, Jeffries, Hart, and Howison 2001). The most used approach to study these *complex systems* is the use of agents with bounded rationality who learn and make their behaviors evolve in time. Following the founding works of (Arthur 1994a) or (LeBaron 1995), who showed that it is possible to make rational global behaviors emerge with simple, bounded individual behaviors, numerous models of markets have been developped. These models aim to reproduce real economic phenomenoms (for example, bubbles and craches: (Levy, Levy, and Solomon 1994), (Lux 1998)) or to study the impact of these phenomenoms on the agents population (Focardi, Cincotti, and Marchesi 2002). The early version of the *Santa-Fe Artificial Stock Market* (also known as SF-ASM) by (Palmer, Arthur, Holland, LeBaron, and Tayler 1994) remains a major reference in this field: it shows that, a global, rational economic behavior can emerge from an agents population that build its behavior on past events, learning and evolution, which is not a commonly admitted result in standard economic theory.

The SF-ASM principle is very simple: agents hold a certain amount of stocks. These assets have a current price and pay at each iteration a dividend. Agents have to take a decision: to invest their cash in new shares or to sell the ones they hold to get their money back. As the price dynamics varies upon the fluctuations in demand and supply, each decision taken by the agents directly impacts the price motion. It has been modified several times to correct some specific aspects of the model (for example the genetic algorithm which allows the agents to make their behavior evolve in time (Ehrentreich 2003), (Gulyas, Adamcsek, and Kiss 2003a)) or to add more realism to the underlying economic logic of the model (LeBaron 2001), (LeBaron 2002). Though, these modifications remain minor technical corrections. We develop our model considering two major modifications of the original SF-ASM: the first improves the agents behavior by putting a stronger economic rationality in their decisions. There, we define two canonical subpopulations: *fundamentalists* and *speculators*. Thus, the second modification consists in mixing those subpopulations to observe and characterize some interesting global market dynamics.

In this article, we want to address the question of markets dynamics, bubbles and crashes using a bottom-up approach. We show that *critical events* may be caused by bounded rationality individuals that ground their behaviors on *market trends* and *liquidity signals*. Our results are consistant with the general thesis of (Keynes 1936) and the french neo-keynesian school of finance leaded by (Orléan 1999). According to those last approaches, critical events are caused by the interaction of rational investors that do not arbitrate prices considering a so-called *fundamental value* but that try to obtain profits in catching the market mood. If they trust the market will raise despite it is yet over-evaluated, they will have a global buying attitude that will therefore push the prices up. The main issue they face is that the market cannot offer enough liquidity if all the agents perform the same decision: thus, if all of them want to sell at the same time, the market breaks down abruptly[1].

The article is organized as follows: a first part presents the architecture of the original model of the *SF-ASM* as well as some minor modifications we bring to it. The second part details the learning process used by the agents to make their decisions and the differences between our two subpopulations of agents, the fundamentalists and the speculators. The last part presents our results and discusses some consequences of this research.

## 2 Market model presentation

Our work is directly based on the articles of (Palmer, Arthur, Holland, LeBaron, and Tayler 1994) and (LeBaron 2002). Let us show common parts as well as differences between the original SF-ASM and our modifications.

[1] as instance, one can report to the *tulipomania* bubble which occured in Netherlands

### 2.1 The original model of the SF-ASM

The model architecture is reduced to the essential: it is composed of one type of stock ($S$) and of $n$ heterogeneous agents $a_1, ..., a_n$: they all have a different behavior. Each step of time can be considered as a market day. Agents do not know at which iteration the simulation will stop. At each step of time $t$, the stock has a current price $p_t$ and pays a dividend $d_t$ per asset to each stockholder. Each agent $a_i$ owns a certain amount of money $m_{i,t}$, and a number of shares $h_{i,t}$. Their goal is to choose between keeping their shares to earn the dividend $d_t$, to sell them to raise their funds or to buy new ones. Another possibility for agents is to invest their cash money in a risk free asset which pays a moderated interest rate $r$ at each step of time $t$.

At the end of each time period, agents are asked their desires: they can either bid to buy new shares (in this case, we have a *bid*: $b_{i,t} = 1$ and no stock offered: $o_{i,t} = 0$), offer a share ($b_{i,t} = 0$ and $o_{i,t} = 1$) or do nothing ($b_{i,t} = 0$ and $o_{i,t} = 0$). We then obtain the cumulated offer ($O_t$) and supply ($B_t$) by summing the $b_{i,t}$ and $o_{i,t}$. The balance between cumulated offer and supply has a direct influence on the stock price and on the quantities exchanged by the agents. If $B_t = O_t$, then all offers and demands are satisfied: each agent who asked for a share receives it and each agent who offered a share sells it. For remaining cases, we have to introduce a process to distribute offered shares function of the number of asks: it is a *market clearing process*. Each agent who asked for a share is given the maximum fraction of share available (offered):

$$h_{i,t+1} = h_{i,t} + \frac{\min(B_t, O_t)}{B_t} b_{i,t} + \frac{\min(B_t, O_t)}{O_t} o_{i,t}$$

One can notice that $b_{i,t} = 1$ do not mean that agent $a_i$ will receive a complete share at $t + 1$, but that he will receive at most a share. Hence, $b_{i,t}$ must be seen as a proposal to buy the maximum fraction of share available. At the end of each time step, the price is updated function to the offer and supply rule (the more the share is asked, the more its price raise) using the following formula:

$$p_{t+1} = p_t(1 + \eta(B_t - O_t))$$

$\eta$ is a parameter which controls the impact speed of the offer and supply on the stock price. Another interesting value is the *fundamental value* of the stock. This value is totally virtual: it has no real existence in the model. Though, it allows to determinate the stock price in an ideal market, which allows to know if the stock is overpriced or underpriced at a given time. It is computed by:

$$\text{fv}_t = \sum_{t=0}^{\infty} d_t(1 + \alpha)^{-t}$$

$\alpha$ is usually considered as equal to $r$. This equation is hence simplified as:

$$\text{fv}_t = \frac{d_t}{r}$$

### 2.2 Modifications on the original model

We have seen that at each step of time, agents receive a dividend $d_t$ per each share. In the original model of (Palmer, Arthur, Holland, LeBaron, and Tayler 1994), the dividend generation process is relatively complex. We have chosen to simplify it by choosing a well known generation process in economics for the generation of random process poorly evolving in time: the random walk (Samuelson 1965). A random walk is defined as follow:

$$d_{t+1} = d_t + \epsilon_t$$

$\epsilon_t$ is a gaussian noise parametered by its mean (null here) and its variance ($\delta^2$).

## 3 Agents reasoning process

As the agents do not know the generation process of dividend $d$ and of price $p$, they are forced to elaborate their strategies only with their experiences (the past values of dividend and prices). Their challenge is to maximize their satisfaction (here, maximize the amount of money won at the end of the game). This is seen here as *trying to recognize a particular market state* to *take the best decision function of this state*. We will describe in a first part which representation the agents use to observe the market, and in a second part how this representation is used to take a decision.

### 3.1 Market representation

Each agent has a stock of $m$ rules which describe market states and tell him which decision to take. A rule is composed of three subparts: the first one describes a specific market state (called *condition part* of the rule). The second part describes the decision to take withing this specific context: bid a share, offer a share or do nothing (called *action part*. The last part represents the current evaluation of the rule's adequateness in market activity (called *force*).

One have to keep in mind that each agent possess his own stock of rule that is, it is hardly possible that two agents are exactly similar.

The $k$-th rule of an agent $a_i$ is composed of:

1. a condition part that can be viewed as a $\gamma$ bit *chromosome* or a string made of $\gamma$ {`0`,`1`,`#`} symbols. Each *gene* or character contributes to the description of a specific market state that is therefore, completely expressed, with $\gamma$ statements. Those statements are said to be true (the value of the gene is `1`), false (`0`) or unrelevant (`#`). The space of conditions is hence $3^\gamma$ size. To give an idea of what a statement is, one can consider the following: *Stock price is over 200$*
2. an action $a_{i,k}$ to take if the rule is selected. We have: $a_{ik} = 1 \Leftrightarrow$ bid one share, $a_{ik} = -1 \Leftrightarrow$ offer one share and $a_{ik} = 0 \Leftrightarrow$ do nothing
3. a strength $s_{i,k}$ which tells how good this rule was in making the agent earning money in the past.

At $t = 0$, the rules are generated following those steps:

1. The condition part is randomly built.
2. The corresponding action is determined following a *rational process* which will be explained further.
3. Initial strengths are 0.

When $t > 0$, the rules are generated, evaluated and updated using a *genetic algorithm*. The genetic algorithm maintains diversity in the rules population, improves them and allows to easily destroy the worst ones.

It is time now to focus on the agents' decision process. Since the agents have to perform the best possible choice, they first identify in their stocks of rules which of them correctly describe the current market state. These rules are said to be *activated*. In other words, the chromosomes are matched against the current market state and a rule is said to be *selectable* if all of its bits (genes) are non contradictory with this state (they are said to be *activated*). Hence, a rule is activated if all of its bits are activated too. A bit $b_i$ is *activated*:

1. $b_i = 0$ and the $i$-th condition of the market state is `false`.
2. $b_i = 1$ and the $i$-th condition of the market state is `true`.
3. $b_i = \#$ and the $i$-th condition of the market state is either `true` of `false`.

Among those activated rules some of them present a positive strength $s_{i,k} > 0$. He then elects one of these rules with a random process proportional to their strength. The action $a_{ik}$ associated with the *elected* rule gives the agent decision. If there are no rules activated by the current market state, then the agent's decision is to stay unchanged ($b_i(t) = 0$ and $o_i(t) = 0$).

At the end of the time step, the agent updates the previously activated rules according to how much money they would have make him earn, giving:

$$s_{ik}(t+1) = (1-c)s_{ik}(t) + ca_{ik}(p(t+1) - (1+r)p(t) + d(t+1))$$

The parameter $c$ controls the speed at which the rules strength is updated.

Each time the genetic algorithm is run, the worst rules (e.g. with the smallest strength) are deleted. They are replaced by new rules generated using a classical genetic process: the best rules are selected to be the parents' of the new rules. A new rule can be generated either by mutation (only a bit of the parent's chromosome is changed) or by a crossover process (reproduction between two parents rules). This mechanism permits, on the one hand, to delete the rules that don't make our agent earn money and to build up new rules using good genetical material. This process is aimed to increase the adaptation of the agents to the market activity.

There are two types of agents in our simulations: some who try to be as close as possible to the fundamental value of the stock (will be refered as *fundamentalist agents* in the following) and some who try to make the maximum benefit without taking care of the fundamental value (will be refered as *speculators agents* in the following). This is a point that largely make our work different from those previously cited. We think that in (Arthur, Holland, LeBaron, Palmer, and Tayler 1997) and (Gulyas, Adamcsek, and Kiss 2003b) one issue is that the decision rules of agents are excessively dominated by randomness: whatever the market statements are, the corresponding action is decided randomly. It is true that along market activity, the evolving process selects best responses to those statements, but nothing grants that the corresponding actions are relevant with respect to an economic logic. For example, it is very probable that although a stock is mispriced (let's say underevaluated), the agents will never try to arbitrate this spread (here with buying it). The other issue is that technical statements as well as fundamental statements are melted and no typical behavior is clearly observable. We try to improve the agent model by defining a minimum economic logic that leads each subpopulation actions: fundamentalists try to arbitrate any price deviation whereas speculators ground their decisions on subjective, technical informations.

Let's consider more closely those two subpopulations.

As said before, the main characteristic of the fundamentalist agents is that they have appropriate decisions considering the spread between the observed prices and the fundamental value. Let's consider the composition of the chrosome and what kind of statements are coded inside.

| Bit | Market Indicator |
|---|---|
| 1 | $p_t/vf_t > 0.2$ |
| 2 | $p_t/vf_t > 0.4$ |
| 3 | $p_t/vf_t > 0.6$ |
| 4 | $p_t/vf_t > 0.8$ |
| 5 | $\frac{p_t}{vf_t} > 1.0$ |
| 6 | $\frac{p_t}{vf_t} > 1.2$ |
| 7 | $\frac{p_t}{vf_t} > 1.4$ |
| 8 | $\frac{p_t}{vf_t} > 1.6$ |
| 9 | $\frac{p_t}{vf_t} > 1.8$ |
| 10 | $\frac{p_t}{vf_t} > 2.0$ |

**Fig. 1.** Fundamentalists' chromosome

| $p_t/vf_t \in$ | Corresponding action |
|---|---|
| $[0.0, 0.8]$ | $1 \Rightarrow$ to buy |
| $[1.2, 2.0]$ | $-1 \Rightarrow$ to sell |
| $[0.0, \gamma\ ]$ with $\gamma > 0.8$ | $0 \Rightarrow$ stay unchanged |
| $[\gamma\ , 2.0]$ with $\gamma < 1.2$ | $0 \Rightarrow$ stay unchanged (ibid.) |
| $[0.0, 2.0]$ | $0 \Rightarrow$ stay unchanged (ibid.) |

**Fig. 2.** Rules for fundamentalist rationalization

Let's consider the seventh gene; the corresponding statement, depending on its value $\{$`1,0,#`$\}$ is: *The price* $\{$`is, is not, is or is not`$\}$ *at least forty percent above the fundamental value*

We have added to the original SASM a *rationalize* procedure. This procedure aims to achieve a minimal economic rationality for the agents. Fundamentalists are assumed to arbitrate significant spreads between fv and $p$, that is to *bid* for underpriced shares and to *ask* for overpriced stock This procedure is based on some rules presented in table 3.1.

One has to keep in mind that this procedure is run each time a new rule is generated (consequently, when the genetic algorithm is initialized and run).

Let's consider now the second subpopulation: the *speculator* agents. As said before, those agents do not arbitrate prices but rather try to make profit using trends or subjective knowledges. Therefore, their chromosome is constructed using this kind of market representations as shown in table 3.1.

| Bit | Market Indicator |
|---|---|
| 1 | $p_t > p_{t-1}$ |
| 2 | $p_t > p_{t-2}$ |
| 3 | $p_t > 1/5 \times \sum_{i=t-1}^{t-5} p_i$ |
| 4 | $p_t > 1/10 \times \sum_{i=t-1}^{t-10} p_i$ |
| 5 | $p_t > 1/100 \times \sum_{i=t-1}^{t-100} p_i$ |
| 6 | $p_t > 1/250 \times \sum_{i=t-1}^{t-250} p_i$ |
| 7 | $p_t > 1/2[Minp_i + Maxp_i]_{i\in[t-1,t-10]}$ |
| 8 | $p_t > 1/2[Minp_i + Maxp_i]_{i\in[t-1,t-100]}$ |
| 9 | $p_t > 1/2[Minp_i + Maxp_i]_{i\in[t-1,t-250]}$ |

**Table 1.** Speculators' chromosome

The chromosome is thought to code general sentiment on the market *trend* which is very different than the identification of a market state. What we mean here is that this trend is supposed to constraint the attitudes of the agents that wants to exploit it, not with an arbitrage strategy but rather in following it. Hence, if the general sentiment is *bull market* a rational behavior for a speculator agent is to buy. (symetrically, if the market is *bear*, the rational behavior is to sell). We have coded this logic in the speculator rationalization. To have a global sentiment on the market trend, we simply appreciate the dominant trend given by the indicators or groups of indicators.

The decision making process for speculator agents is relatively complex and can be divided into two major steps.

For bits 1, 2, 7, 8 and 9, we simply consider if the belief of the agent validates the condition or not. Let's consider the example of bit 8: we explicitly test if the price is over or above the median of the interval bounded by the highest and the lowest quotation during the lasts 100 days. If the price is above, it is thought that the price will decrease and alternatively, if it under this median, it is believed that the price will rise. As instance, this last situation pushes the agent to bid new shares. Bits 3 to 6 receive a special treatment: bits 3 and 4 are considered together as well as bits 5 and 6. The first pair allows the estimation of short range trend while the second pair allows the estimation of a long range trend. pairs, $bit_i$ is the first one e.g. bit number 3 and bit number 5 while $b_{i+1}$ is the second one e.g. 4 and 6. To appreciate the trend, one has to consider the situation of the current price relatively to those bits. As example, let's consider the situation where the chromosome's bits 3 and 4 are respectively 0 and 1. In this case, it is false to assert that the current price is above the mobile average on the past five days whereas it is clearly above the mobile average on the past ten days. We therefore consider that this information is not sufficiently clear to influence the decision and bid and ask positions have to be weighted with the same absolute value scalar: 0.5. When those bits are respectively

1 and 1, the trend is clearly *bull* and the agents will be temptated to follow it, e.g. to buy. The nine possibilities for each pair are summed up in table 3.1.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $bit_i$ | 1 | 0 | # | 0 | 1 | # | # | 0 | 1 |
| $bit_{i+1}$ | 1 | 0 | # | 1 | 0 | 0 | 1 | # | # |
| Partial rationalization | 1 | -1 | 0 | {0.5, -0.5} | {0.5, -0.5} | -1 | 1 | -1 | 1 |

**Table 2.** Speculators' rationalization when $i \in \{3, 5\}$

A first step in the speculators' rationalization process is then achieved: our agent can form an initial belief on the possible tendency of the market summing the values of each indicator. One has to keep in mind that some of them are positive (giving bid signals) negative (ask signals) or null (do nothing). If the number of positive signals is dominating, the initial belief will be that the price will probably rise and the corresponding behavior will be to bid. Symmetrically dominating negative signals lead *to ask* and null signals lead *to stay unchanged*.

One can easily imagine that such a logic may lead to constantly growing or falling markets: *bear* signals are followed by bid positions that push the price up. Why this tendency should break down ? According to Orléan (1999), one major indicator observed by the traders is *market liquidity*. The idea is that operators are very concerned with the possibility of clearing their positions (to sell when they hold stocks or to buy if they are short). This implies that minimum volumes are realized at each time step. When the market becomes illiquid, agents may be stucked with their shares. Therefore, they follow the market only and only if they are confident on the liquidity level of the market. This point has been included in the agents' logic with the following rules:

- each agent has her own treshold above which she considers that the market is unsufficiently liquid to clear her positions.
- When this threshold is reached, she adopts a position opposite to the one she would have adopted without considering this treshold. By the way, she decides to reverse her investment strategy to go out of the market.

## 4 Experimental schedule and results

As the model contains many numerical parameters, we have chosen to only vary the ones which directly impacts the global price dynamics, that is to say the speculator agents proportion and their liquidity fear parameters. The other ones are considered as constant as they can be seen as more technical model parameters. All of the following experiments are realized on a time range of 10000 iterations. Though, as the genetic algorithm used by the agents to adapt themselves to the market needs a learning period, only iterations between time step 2000 and 10000 are shown. All statistics are conducted on this range unless the opposite is mentionned.

As our primarly goal is to study the influence of speculator agents' proportion on price dynamics, we first run an experiment without speculators (i.e. only with fundamentalists). This first experiment allows us to validate our fundamentalist agent model by matching the experimental results with the ones obtained by (Palmer, Arthur, Holland, LeBaron, and Tayler 1994) with the original SF-ASM model. This experiment will also be used as a comparison base with other ones as it represents the baseline price dynamics of our model (i.e. with the less variant price series). Other experiments are realized by gradually increasing the speculator agents proportion in the agents population and by adjusting their liquidity fear. Many experiments have been run, but we only detail here the ones with the more significant results.

### 4.1 A fundamentalist market

The following figure represents the price and fundamental value motions when the market is only made of fundamentalist agents.

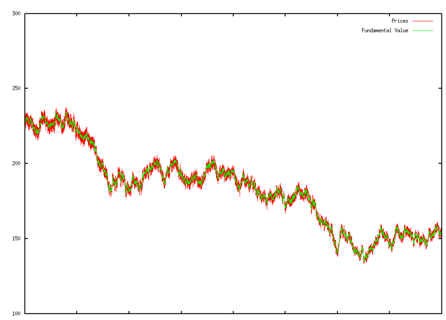


**Fig. 3.** Market dynamics with fundamentalist agents

The first step to test if those motions are somewhat consistent with what happens in the real stock markets consist in testing whether they are driven by non-stationary processes or not. The appropriate test to seek for a random-walk process in market returns is an Augmented Dickey-Fuller unit root test (*e.g.* ADF). Both fundamental values and prices have to be random walks if we want to qualify the simulations *realistic* since the immense part of academic researchs attest such motions for modern, real stock market dynamics.

The Null and the alternative hypothesis are: In the following tests, the Null is *time serie presents one unit root* ($H_0$) while the alternative is *time serie has no unit root* ($H_1$). Table 4.1 reports the results of those tests. Interpretation is the following: if t-Statistics is less than the critical value, one can reject the $H_0$ against the one-sided alternative $H_1$[2].

[2] Regressions with intercept and trend, and automatic lag length selection, modified Hannan-Quinn criterion.

| | | time series | t-Statistics | Prob.* |
|---|---|---|---|---|
| Augmented Dickey-Fuller test | fund. val. | -2.3594 | 0.4010 | |
| Augmented Dickey-Fuller test | price | | -2.4154 | 0.3713 |
| Critical values | 1% level | -3.9591 | | |
| | 5% level | -3.4103 | | |
| | 10% level | -3.1269 | | |

*MacKinnon one-sided p-values.

**Table 3.** Augmented Dickey-Fuller Unit Root Test for Fundamental Values serie and Prices serie

Johansen co-integration test shows that prices and fundamental values co-evolve. We also observe that the spread between prices and fundamental values remains very weak (between -3.22% and +2.72% with a 0.02% mean and a 1.11% standard deviation). This base line experiment exhibits therefore some interesting results if one considers its proximity with real market dynamics. It also shows that bounded rationality agents can make emerge a random walk motion that is characteristic of efficient prices on stock markets. This result is already documented by (Palmer, Arthur, Holland, LeBaron, and Tayler 1994),(Arthur 1994b). Nevertheless, our contribution is to obtain such results with agents following rules that make sense, which was less evident in the original studies.

### 4.2 A mixed market

Figure 4 represents price and fundamental value motions when the market is made of 25% of fundamentalist agents and 75% of speculators. It appears that the market is

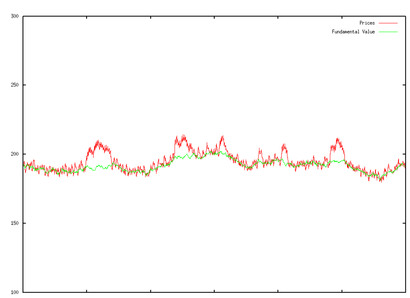

**Fig. 4.** Market dynamics with 25% fundamentalist and 75% speculators

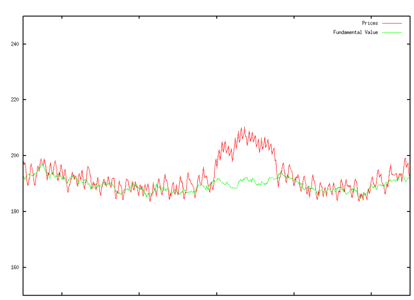

**Fig. 5.** Detail of a bubble

more volatile when it is flooded with fundamentalists which is an expected result. If one considers the statistical properties of the price motion globally (on the complete sample), it appears that a Null hypotheses of random walk can be rejected with a very low risk (with $p < 3\%$). This result is understandable as the agents population is composed of a majority of speculators. Though, on smaller samples (for example on time range from 2000 to 3000), the result of the test is inverted: the market is in a period where it behaves as if it follows a random walk. In such periods, the price and the fundamental value motion are co-integrated, which shows that market follows the fundamental value dynamics.

| | Price deviation with fundamentalists | Price deviation with speculators |
|---|---|---|
| Mean | 0.032079 | 2.135464 |
| Median | 0.116219 | 1.259602 |
| Maximum | 5.377301 | 19.94562 |
| Minimum | -6.506877 | -5.811743 |
| Std. Dev. | 2.067116 | 3.809237 |
| Skewness | -0.200899 | 1.191886 |
| Kurtosis | 2.421358 | 4.609048 |

**Table 4.** Prices deviations comparison

In Table 4.2, we have reported some basic statistics related the spreads between observed prices and fundamental values. It clearly appears that prices are much more volatile in the second regime (with speculators) than in the first one (standard, maximum and minimum deviations). The over-returns mean is also strictly positive. Moreover, returns distribution does not follow a Normal distribution.

| | Price deviation with fundamentalists | Price deviation with speculators |
|---|---|---|
| Mean | 0.152548 | 3.180839 |
| Median | 0.150780 | 1.450169 |
| Maximum | 4.326421 | 19.12118 |
| Minimum | -5.099582 | -4.708662 |
| Std. Dev. | 2.114522 | 5.535200 |
| Skewness | -0.230643 | 1.228508 |
| Kurtosis | 2.236049 | 3.489872 |

**Table 5.** Prices deviations comparison during a critical regime

Let's focus on a critic period where we can visually identify a *bubble*, for example during time period from 5000 to 5400. During this period, prices are still a random walk. In Table 4.2 are shown prices deviations during a bubble. We can notice that on such a period, the standard deviation is greater than the one observed on the complete time range as in Table 4.2. A bubble is hence characterized by a great deviation between the stock price and its fundamental value during a long time range. The kind of dynamics shown in Figures 4 and 5 are obtained with a simulation involving 75% of speculators and 25% of fundamentalists and a specific random generator seed, but such dynamics also appear with other sets of parameters as long as speculator agents proportion is great ($> 70\%$ of total agent population).

In the speculative regime (when speculators compose the main part of population), we obtain a highly volatile price dynamic with bubbles and crashes. These phenomenoms would rather be undetectable if we could not watch the fundamental value. Moreover, as the prices follow most of the time a random walk, nothing can distinguish such a dynamic from the one observed with a fundamentalist population except the comparison between the prices and the fundamental value. Hence, there could be speculative bubbles in real market dynamics as the technic effiency of the market would be respected. In this case, only great prices deviations would be named as bubbles a posteriori.

## 5 Conclusion

In our simulations, we obtain price dynamics specific to our two agents populations. These behaviors were designed to illustrate two main economic logic : the first follows the classical economic theory which is grounded on agents arbitrating differences between the fundamental values and the current stock prices, whereas the second is mainly based on ideas from the keynesian theory of speculation (see (**?**)).

The first market dynamics is obtained when the agents population is only composed of fundamentalists. We show that in this case, the price dynamics follows a random walk which co-evolve with the fundamental values. This first result can be related to the ones of (Palmer, Arthur, Holland, LeBaron, and Tayler 1994): inductive agents in bounded rationality can make efficient prices emerge. The difference here is that fundamentalists only ground their decisions on classic market indicators and that these decisions are made following constitent behavioral rules, which is not the case in many simulated stock markets.

When speculator agents compose the main part of the agents population, we obtain another type of dynamics: prices still follow a random walk process, but during some periods, the system reaches a critical state. This critical state is characterized by the emergence of a new phenomenom: the stock starts to be more and more overpriced (bubble) before falling back violently to its fundamental value (crash). Moreover, these market dynamics are very volatile.

Next steps in our research could be to introduce a third agent behavior which will act as a market regulator to arbitrate the market and prevent bubbles from happening. This could for example be realized by introducing a behavior who would ponctually decrease the market liquidity to force the speculators to reverse their decisions. One can also imagine to study the impact of social interaction between agents on market dynamics to see if it would arbitrate the price deviations or amplify them.

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