# A Simulated Stock Exchange Market : First Results

L. Neuberg, K. Bertels
University of Namur, dept. of Business Administration
Rempart de la Vierge 8, 5000 Namur, Belgium

**Abstract**

In this paper, we present a model that simulates the behaviour of a heterogenous collection of financial traders on a market. Each trader is modelled as an autonomous, interactive agent and the agregation of their behavior results in market behaviour. We specifically look at the role of information arriving at the market and the influence of heterogeneity on market dynamics. The main conclusions are that the quality of the information determines how the market will behave and secondly, heterogeneity is required in order to find the right statistical properties of the price and return time series.

## 1 Introduction

In this paper, we present a model that simulates the behaviour of a heterogenous collection of financial traders on a market. Each trader is modelled as an autonomous, interactive agent and the agregation of their behavior results in market behaviour. We emphasize that the main goal of the paper is not to predict the future evolution of any stock, but rather to gain a deeper understanding of the phenomena observed in financial markets.
The main contributions of the paper are the following :

- The simulations suggest that the information arriving at the market determines to a high degree how the market will behave.

- Furthermore, it appears that in introducing heterogeneity, the overall market dynamics changes. An even stronger claim is that only by introducing heterogeneity does the model reproduce a market dynamics similar to real world financial price dynamics.

The paper is organized as follows. We first introduce the model and explain how each agent is modelled and how their interaction results in the overall market behavior. We then present the results of three simulation runs.

# 2 Description of the Model

## 2.1 The Agent's Behaviour

We distinguish between different kinds of traders on the market, each having their own rationality and knowledge. As any financial trader, the agent must be able to evaluate an action and form an expectation with respect to its future price. On the basis of this expectation, he will propose a price to sell or buy a particular stock. This offer can then be evaluated by other traders on the market. These expectations are the result of some kind of reasoning and decision making. Depending on the success of the proposed transaction, measured in terms of financial profit, he will modify his decision rules and thus learn.

### 2.1.1 Model of an agent's behaviour

**Decision making and expectations formation** as explained above, each agent needs to be able to decide whether he wants to buy or sell a particular stock, and at what price. He therefore needs to have decision rules that allow him to make some kind of expectation as to the future evolution of the price. He will do so on the basis of information at his disposal. In our model, we have chosen to implement a classifier system where different decision rules are represented as if-then rules. At a given moment, if a condition of his set satisfies the present situation in the environment, the agent will take the corresponding action. The condition of each rule is a chain of characters(" 0 ", " 1 ", or " # ") determining whether the rule is equivalent to the market situation. This equivalence is achieved if the characters along the chain of the condition are similar to the characters along the chain of the market situation. In the case of character " # ", there is always equivalence to the extent that it expresses

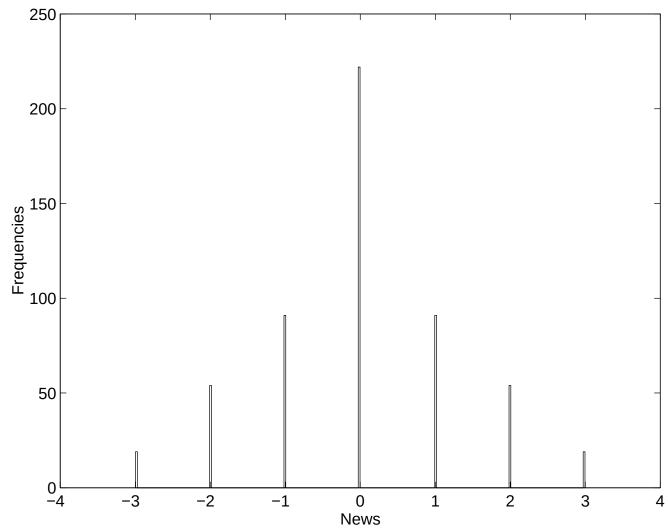


Figure 1: The Information Frequency Distribution

the indifference between the characters " 1 " and " 0 ". As for the action, it is a chain of characters representing the value of two parameters $a$ and $b$ in binary fashion. These parameters allow to compute the expected future prices and dividends in the following way : $E[P_{t+1} + d_{t+1}] = a(P_t + d_t) + b$. For each agent, a set of rules allowing to calculate these expected prices and dividends will be generated using genetic algorithms. Initially, 900 rules are generated. This number will be reduced during the learning process.

**Learning :** in this original set of 900 rules, some may be more efficient than others. Those rules yielding more accurate expected prices and therefore a higher financial gain will have a higher reproduction rate and a higher probability to survive. The frequency of the re-actualization of the rules will depend on each agent's ability to learn.

### 2.1.2 Model of the market

**Information :** as in real life, expectations with respect to prices and dividends are largely influenced by information arriving on the market. In our model, information arrives at the market at regular intervals of time. This information may vary from 'very negative (-3)' over 'neutral (0)' to 'very positive (+3)'. Figure 1 represents the distribution of the different kinds of news flashes. We emphasize that not every agent may interpret the same piece of information in the same way.

**Price formation and market clearing :** Intersecting orders to buy and sell are going to create the dynamics of asset prices (see Figure 2). The market clearing mechanism is similar to the one used in [ART96] in which bids are continuously resubmitted until a price is formed that clears the market. At each period of time, the agents try to optimize the allocation of risky and non-risky assets. Initially, the price and dividend previsions made by agent $i$ at time $t$ are normally distributed with an average of $E_{i,t}[p_{t+1} + d_{t+1}]$ and a variance $\sigma^2_{t,i,p+d}$. Demand (or supply) by agent $i$ at time $t$ is given by :

$$x_{i,t} = \frac{E_{i,t}(p_{t+1} + d_{t+1} - (1+r)p_t)}{\lambda\sigma^2_{i,t,p+d}} \tag{1}$$

where $p_t$ is the price of the asset at time $t$ and $\lambda$ is the degree of risk aversion.

In order to close the system, total demand must be equal to the number of available goods on the market :

$$\sum_{i=1}^{N} x_{i,t} = N \tag{2}$$

# 3 Simulation Results

In this section, we present the different simulations and give a plausible interpretation of the observed behaviour. However, we first start by defining the general approach used in our simulations.

## 3.1 Some Preliminary Remarks

Before starting the actual simulations, we have allowed each agent to modify his decision rules on the basis of an artificially generated set of data. The goal of this "mode setting" is twofold : in that way, we can already reduce the 900 rules to a more manageable couple of hundreds. And secondly, most of the rules obtained as the result of the learning process, will already make more sense than the original ones who were generated randomly.

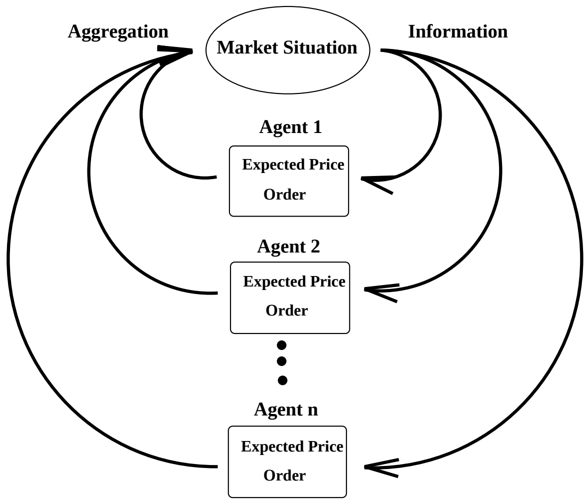


Figure 2: Aggregated Market Behaviour

It is important to emphasize that we are currently not looking at real world markets. The main reason is the lack of good empirical data in which the price evolution of any financial asset is linked to information arriving on the market (such as news flashes from Bloomberg or Reuters). We therefore impose a particular market behaviour. This means that we generate a time series, representing the price evolution in function of a particular information vector. To this purpose, an artificial time series is generated, using the following equation :

$$P_t = (1 + \alpha I_{t-1}) P_{t-1} \tag{3}$$

where $I_{t-1}$ represents the information and P is the price. Once the agents have learned this mechanism the actual simulations can start. In the remainder of the paper we will use the following terms :

- Normal Agents : are those agents that will have learned this mechanism of how to use the information to compute a future price.
- Perturbating Agents : are those agents who will deviate from this mechanism.
- Reference Time Series : this is a time series computed using equation 3 on the basis of a new information vector.

- Generated Time Series : these are the ones generated by the interacting agents.

For each of the simulations, we compute the following statistics :

- correlation coefficient between the reference time series of the prices and the generated one. The standard deviation measures price volatility.
- Skewness and Kurtosis are computed on the returns. A positive skewness and positive excess kurtosis are characteristic for real world financial data.

## 3.2 Simulation 1

In this simulation, we modelled 10 agents having different sets of parameters (a and b) and each having his learned set of decision rules. The information vector used for this simulation is different than the one used during initial learning. If the agents have learned well the price dynamics during the initial learning phase, we expect that they should be able to reproduce similar (but differerent) dynamics. The differences could then be primarily due to the differences in the exogeneous variable $I_t$. The price dynamics is given in Figure 3. The correlation coefficient between the reference time series and the generated time series is 0.95 which shows a great similarity between the two. The skewness is negative but very small, indicating that the distribution of the returns is quasi normal. A positive excess kurtosis implies that the distribution is peaked. This seems to imply the following :

- the agents reproduce the correct dynamics. This claim is supported by the correlation coefficient of 0.95 (See Table 3.5 which summarizes the different simulations).
- The interaction on the market does not introduce a higher (positive) skewness even though the returns have a peaked distribution.
- We might also advance that the agents are apparently applying the decision mechanism they were taught.

## 3.3 Simulation 2

We now investigate whether or not the presence of perturbating agents can influence the market in such a way that the dynamics change. To this purpose, we introduce one agent that

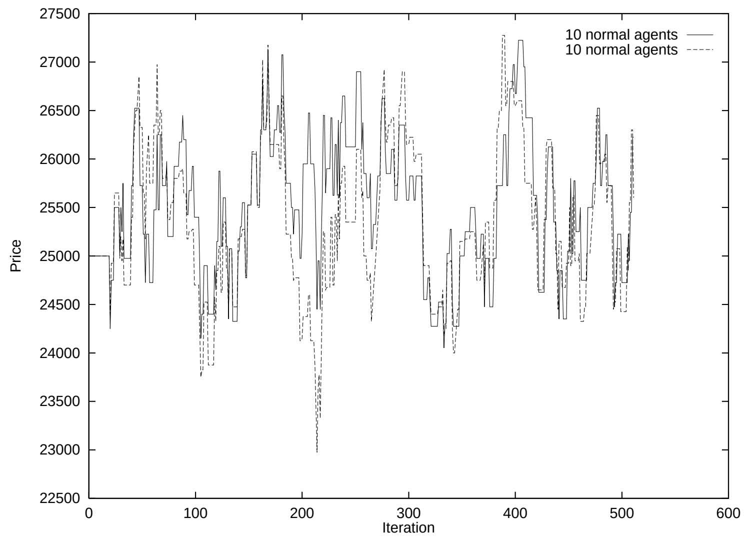


Figure 3: Price Dynamics of Simulations 1 and 2

will systematically react differently than the others. His interpretation of the information arriving on the market will be different, pushing him to make a different decision. The simulation counts the same number of periods and the same information vector has been used. This way, we can better compare the resulting prices with the time series of the previous simulation. As we can observe from Figure 4, the two series are quite distinct. This observation is confirmed by the correlation coefficient which has dropped to 0.7. The volatility increases from 697 to 771, as measured in terms of standard deviation. We now also observe the fat tail in the returns (skewness of 0.266) as well as a peak (excess kurtosis of 1.452). and the market does not seem to be reacting in a systematic way to news flashes. The following can be concluded :

- The lower correlation coefficient seems to indicate that the market behaves differently (is in a different regime) whenever there is more heterogeneity.
- The volatility increases although a potential explication for this could be that once a certain portion of agents starts behaving differently, their actions are balanced and their influence on the price is compensated.

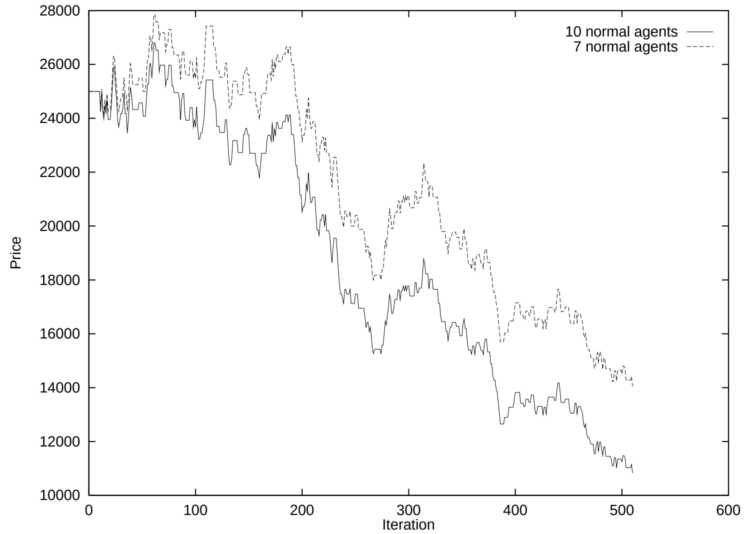


Figure 4: Price Dynamics of Simulation 3 and 4

- We now observe for the first time a positive skewness and a high excess kurtosis. We could say that only now do we seem to have a replication of real world financial dynamics.

### 3.4 Simulation 3

We now introduce a new information vector as the basis for the market dynamics. Rather than looking at a normal market situation, where there is no dominant trend in the information, we now simulate the situation in which bad news arrives at the market in a more or less constant way. The distribution of the information is given in Figure5. As we can observe from Figure 4, there is a clear negative trend in the market. We also see from the computed standard deviations, that the volatility has increased drastically (from 697 to 4755) which is in concordance with reality. Markets in crisis behave always more nervously than markets in a normal state. We also see that the correlation coefficient is still very high.[1] This leads us to suppose that still the same underlying decision taking mechanism is applied. However,

[1] We now use as reference time series one that uses the same 'bad news' information vector as a point of comparison.

skewness and kurtosis have dropped again to negative values.

### 3.5 Simulation 4

We again introduce a number of perturbating agents who are different than the perturbating ones in simulation 2. The heterogeneity is introduced by imposing these agents to attach less importance to very negative information. The information arriving at the market is the same as in the previous simulation. As we can see from Figure 4, the market trend is downward. Both the correlation coefficient (0.97) and the volatility (4011) are still very high. compared to the normal situation . We again observe that in the case of heterogeneous agents, the skewness becomes positive, even though the kurtosis is negative. The following conclusions can be advanced :

- Analogously to simulation 2, we observe that in introducing heterogeneity in the agents, the generated time series has properties similar to those of real world financial data.
- We furthermore see that the constant inflow of bad news, causes the market to crash. The price dropped 50% and volatility, compared to the volatility of simulation 2, has risen with a factor of 5.

Table 3.5 summarizes the results of the 4 simulations.

| Simulation | Information vector | # Normal Agents | # Perturb. Agents | Standard Deviation | Skewness | Excess Kurtosis | Corr. Coeff. |
|---|---|---|---|---|---|---|---|
| **RTS** | IV1-Normal | 10 | 0 | 73 | -0.05 | 1.24 | 1 |
| **1** | IV2-Normal | 10 | 0 | 697 | -0.051 | 1.234 | 0.95 |
| **2** | IV2-Normal | 7 | 3 | 771 | 0.266 | 1.452 | 0.70 |
| **RTS** | IV3-Crisis | 10 | 0 | 4694 | -0.02 | -0.05 | 1 |
| **3** | IV3-Crisis | 10 | 0 | 4755 | -0.054 | -0.126 | 0.99 |
| **4** | IV3-Crisis | 7 | 3 | 4011 | 0.17 | -0.17 | 0.97 |

## 4 Conclusion and Further Research

In this paper, we have presented some preliminary results of the simulations with an artificial financial market. The main conclusions are that information plays a crucial role in the way

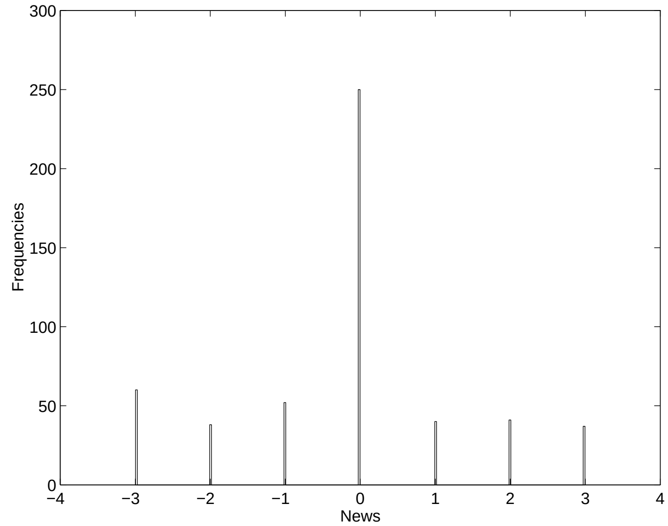


Figure 5: The Distribution of Information : Crisis

the market behaves. Each set of simulations clearly shows a different behavior of the market when different information sets are used. The second main conclusion is that only when introducing heterogeneity amongst the agents, does the model generate a market dynamics which exhibits similar characteristics as real world financial markets. Further research is needed to confirm the above results. One of the things one might look at is what the influence is of different proportions of normal and perturbating agents. [2]

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