# Artificial Agents and Speculative Bubbles

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## Abstract

Pertaining to Agent-based Computational Economics (ACE), this work presents two models for the rise and downfall of speculative bubbles through an exchange price fixing based on a double auction mechanism. The first model is based in a finite time horizon context where total expected dividends decrease along with time. The second model follows the *greater fool* hypothesis: an agent behaviour depends on the comparison of its estimation of risk with that of a virtual greater fool. Simulations shed some light on the influent parameters and the necessary conditions for the appearance of speculative bubbles in an asset market within the considered framework.

*Keywords : Agent-based markets, Speculative Bubbles, Zero Intelligence traders.*

## 1 Introduction

Beyond the standard economic models, traditionally centered on Rational Expectations Equilibria [11] and efficient markets, several new paths have recently been explored to tackle the otherwise unexplainable phenomena underlying speculative bubbles. Having an idea of what is behind these phenomena is crucial as they question the ability of existing markets to perform efficient resource allocation. Their understanding is a necessary first step on the way leading to the design of safer market structures.

One approach for investigating speculative bubbles is Experimental Economics, as pioneered by Vernon Smith; several studies [14, 10] demonstrate the rise and downfall of speculative bubbles in closed and controllable laboratory environments involving candid and/or experimented human beings. Such experiments also offer room for studying the effects of information cost and/or sociological noise (or cognitive dissonances).

Another approach is Agent-based Computational Economics (ACE; see [15] for a survey). This bottom-up approach, based on Artificial Intelligence (AI)-oriented models of economic agents, replaces experiments by computational simulations. It also offers a controllable framework for studying the emergence and dynamics of global patterns from the repeated interaction of elementary agents endowed with limited perception, communication, cognitive and learning abilities. Financial markets have been studied intensively along these lines (see [7, 8, 13]), and some inspirations for the present work will be discussed in Section 2.

Pertaining to the ACE field, this paper investigates two models for boundedly rational agents, inspired from Duffy and Unver's work [5]. Likewise, we consider Stochastic-Zero-Intelligence (SZI) agents, whose bids and asks are randomly drawn from a price distribution depending on the previous exchange price. The difference lies in the distribution setting strategy chosen to explain speculative bubbles.

Two strategies are enforced with respectively finite and infinite time horizons. In the first setting (exogenous risk), the risk straightforwardly depends on the expected dividends. In the second setting (endogenous risk), the agent strategy is determined from the comparison between the estimated risk, and the agent and *greater fool*'s risk thresholds. Depending on this comparison, the agent's strategy is exuberant, comfortable, or panicky, thereby ruling its propensity to buy or sell shares as well as its bid and ask distribution.

The paper is organized as follows. After briefly reviewing some related works (Section 2), we describe the market mechanism and the agent models (Section 3). Section 4 reports on experimental simulation results, and discusses the necessary conditions and influent parameters with respect to bubble dynamics. The paper ends with perspectives for further research.

## 2 Related works

Let us briefly review some sources of inspiration for the present work. Beltratti and Margarita [4] consider an artificial market where individual agents try to maximize their expected return by following a price forecasting mechanism based on artificial neural networks. To obtain more precise forecasts, costly information acquisition is possible with respect to the number of neurons in the NN's hidden layer and to the length of agent memories. As agents might decide to invest in a simple, average or complex price estimate, one can observe the general market behaviour and the dynamic distribution of simple, complex and other agents.

Arifovic [1] proposes a 3-parameters agent model, governing the exchange rate between two currencies. The three parameters are evolved along a simple Genetic Algorithm. One major interest of this work is to reproduce the market behaviour observed in experimental economics (oscillations), contrasting with the dynamics predicted by rational expectation theory.

In the famous "El Farol" problem [2], another dimension for bounded rationality appears, namely the anticipation of other agents decisions. Each agent will decide to go to the bar, if and only if it expects the bar to be reasonably crowded (follow the minority rule). Along the same lines, the Santa Fe artificial stock market [3, 6, 9] provides a unified framework where agents are endowed with forecasting rules (evolutionary classifier systems). Depending on the evolution pace, the market switches from an efficient to a speculative behaviour.

## 3 Overview

The market considered in the following involves a finite set of agents, trading a single asset.

### 3.1 Exchange rule

The exchange rule is based on a *double auction* mechanism (Table 1). Each novel ask (respectively bid) is confronted to the selling (resp. buying) order book. It succeeds if it is greater than the minimum selling order (resp. lower than the maximum buying order); in such a case, the exchange price is set to the minimum selling order (resp. maximum buying order), and this order is removed from the book. Otherwise, order books are updated with the novel ask or bid offer.
Order books contain at most one offer from each agent (*cleared book* convention).

| | |
|---|---|
| **Init**: Initialize agents; Buying order book = {}; Selling order book = {}; | |
| **Loop**: For $t = 1..T$ | *auction round* |
| For each agent | *random permutation* |
| $Order(bid \vee ask \vee idle; value)$ = strategy(agent) | *Section 3.2* |
| If $Order$ succeeds | |
| Exchange price = $P_{currentBest}$ | |
| Refresh order book | |
| Else | |
| Update ($Order$, order Books) | |
| $p_t$ = Average exchange price over the auction round | |

Table 1: Double Auction Market Clearing Algorithm

### 3.2 Individual agents

Agent $i$ is characterized from its belongings, cash and number of shares noted $cash(i,t)$ and $shares(i,t)$.

In each auction round, the agent decides between buying one share, selling one share, or remaining idle. This choice depends on its strategy, which is governed by its estimation of the risk currently held by the market. The agent model thus depends on i) a risk estimation function; ii) a strategy mapping risk into a decision (buy $OR$ sell $OR$ remain idle) and a price offer.

#### 3.2.1 Exogenous Risk – homogeneous Agents

A straightforward strategy is based on the finite time horizon, where the propensity to buy decreases as the game comes to an end. The risk function linearly increases from 0 at time $t = 0$ up to 1 at $t = T$. All agents either buy or sell, and the probability of selling increases with the risk along a linear, sigmoid or exponential function $f$ (Section 4).

The pricing strategy, inspired from the anchoring effect [5], follows a uniform distribution centered on the previous exchange price $p(t-1)$. If $U[a,b]$ stands for the uniform distribution on segment $[a,b]$,

$$Order(t; buy \vee sell; value) : \begin{cases} Pr(sell) = 1 - Pr(buy) = f(\frac{t}{T}); \\ \\ value \propto U[.99p(t-1),\ 1.01p(t-1)]. \end{cases}$$

Clearly, this model suffers from two shortcomings. On one hand, although finite time horizons are consistent with experimental economic settings (e.g. [14, 12, 10]), they are not with respect to actual markets. Second, this model offers limited insights into the causes of speculative bubbles as the market behaviour is ultimately controlled from the exogenous risk function; a variety of price curves can be obtained through the carving of function $f$.

#### 3.2.2 Endogenous Risk, Heterogeneous Agents

To get rid of the aforementioned limitations, a more sophisticated model, involving a naive form of technical trading, was designed. An individual risk function is attached to each agent ; this function depends on the exchange price history and can be tuned through 2 agent parameters.

More specifically, the elementary risk is a weighted sum of two terms: the distance between the current price and the asset fundamental value noted $F$, and the slope of the price curve $\frac{dp}{dt}$ (averaged on the 3 previous time steps).

The first term accounts for potential arbitrage profits: risk increases as the exchange price gets higher than the asset fundamental value and vice-versa. The second term reflects the "greater fool" hypothesis and the propensity to follow recent trends: a steep increase in prices suggests further increase and potential trade with greater fools whereas negative slopes are seen as a warning sign. The weights associated to both terms, noted $v_i$ and $w_i$ reflect the risk preferences of the $i$-th agent.

The elementary risk is taken through a sigmoid, ensuring that the risk estimate varies smoothly in $[0, 1]$:

$$r(i,t) = \frac{1}{1 + ae^{-r_e(i,t)}} \qquad r_e(i,t) = v_i(p(t-1) - F) - w_i \frac{dp}{dt}$$

The slope of the sigmoid (factor $a$) controls the transition between the low and high risk regions.

#### 3.2.3 Order strategies

The agent risk function is compared to two thresholds: the agent risk threshold $R_i$ and the fool's threshold $\alpha_i \times R_i$ $(\alpha_i > 1)$.

Depending on the comparison, the agent uses one among the three following strategies:

**Exuberance** When the risk is smaller than the agent risk threshold ($r(i,t) < R_i$), the agent buys a share with probability 80%; otherwise, it stays idle or sells a share with equal probability (10%).
The price offer is drawn from the uniform distribution centered on the previous exchange price $U[.99p(t-1),\ 1.01p(t-1)]$.

**Comfort** Otherwise, if the risk is smaller than the fool risk threshold ($R_i < r(i,t) < \alpha_i \times R_i$), the agent stays idle (no bid and no ask) with probability 50%; otherwise it either buys a share (probability 40%) or sells a share (probability 10%). The price offer is again drawn from distribution $U[.99p(t-1),\ 1.01p(t-1)]$.

**Panic** Last, if the risk gets higher than the fool risk threshold ($\alpha \times R_i < r(i,t)$), the agent sells with probability 90%, otherwise it stays idle or buys a share with equal probability (5%).
Price offers are determined similarly except in the very last experiment stated below where, to account for panic effects, the price offer is drawn from distribution $U[.95p(t-1),\ p(t-1)]$.

To summarize, each agent involves 4 internal parameters: its risk preferences (weights $v_i$ and $w_i$ of the distance to the fundamental value and the price slope), and its risk threshold (the agent risk threshold $R_i$ and the fool factor $\alpha_i$).

For each auction round, the individual risk is computed for every agent and turned into an order strategy depending on the agent thresholds. The exchange price is determined by the double auction mechanism (Section 3.1).

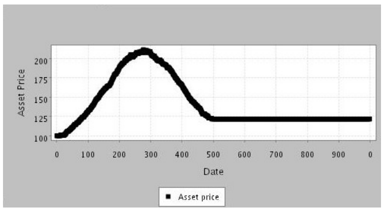



Figure 1: Exogenous risk: Linear rise and fall above the fundamental value

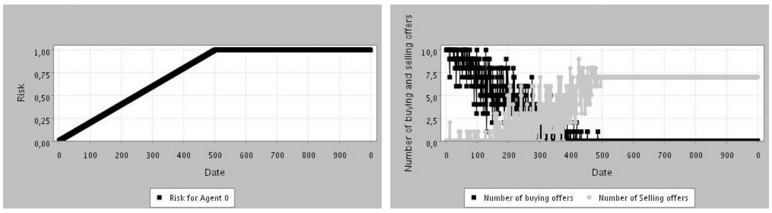



Figure 2: Exogenous risk: (left) Risk function linearly increasing with time (right) Black: selling offers ; Grey: buying offers

## 4 Experimental results

The experimental goal is to study the dynamics of the price curve associated to the above models, and to determine the factors related to a speculative bubble.

The artificial market was simulated for 10 agents during 1,000 auction rounds. Initially, all agents are endowed with 1,000 cash units and a number of shares uniformly drawn in $[0, 10]$. The fundamental asset value is set to $F = 100$ (further studies are concerned with attaching each agent with an estimation of the fundamental value). The simulation, written in Java, takes around one minute on a Pentium-IV, 1.8 GHz PC.

### 4.1 Exogenous risk

As could have been expected, the price curve in the exogenous risk, homogeneous agent model straightforwardly reflects the risk function; depending on whether $f$ is linear or sigmoidal, one obtains a symmetrical rise and fall of the price (Fig. 1 and 2) or an exponential rise followed by a steep crash. On can however notice on fig. 1 that prices do not exactly fall back to 100. This can explained by the intrinsical latency of the auction mechanism and can be corrected by allowing the trading game to last a little longer.

Overall, these experiments only serve to demonstrate the consistency of our double auction market.

### 4.2 Endogenous Risk

A large diversity of market behaviours is observed along the different settings.

#### 4.2.1 Homogeneous Agents

In a first setting, all agents are given the same parameter values ($v_i = 1; w_i = 3; R_i = .5; \alpha_i = 1.1$).

In this case, an efficient market behaviour is observed (Fig. 3). The exchange price hardly deviates (2 or 3%) from the fundamental value $F$. Further, it quickly adapts to re-estimation of the fundamental value (e.g. as $F$ is decreased from 100 to 75 at iteration 250, Fig. 4).

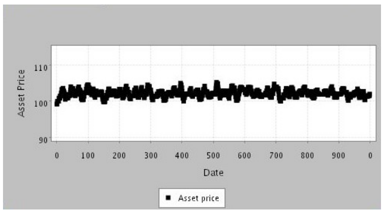



Figure 3: Prices in the Exogenous risk and Homogeneous Agents case : An efficient Market

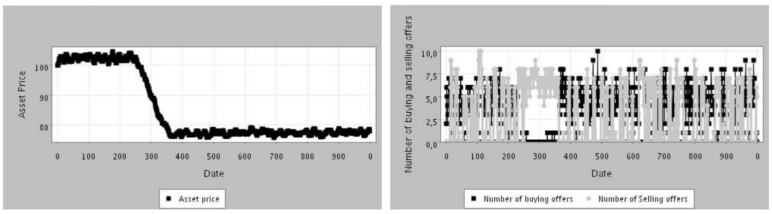



Figure 4: Homogeneous Agents: the exchange price adapts to the fundamental value when $F$ decreases to 75 at iteration 250. (left) Price curve (right) Black: selling offers ; Grey: buying offers.

### 4.3 Agents With Heterogeneous Risk Thresholds

In a second experiment, the agent threshold risk is initialized from the uniform distribution $U[.4, .8]$. All other agent parameters are set to the same default values as above.

The heterogeneity of the risk thresholds significantly degrades the the market efficiency, as can be observed from Fig. 5. The exchange price oscillates around 120 (significantly higher than the fundamental value $F = 100$).

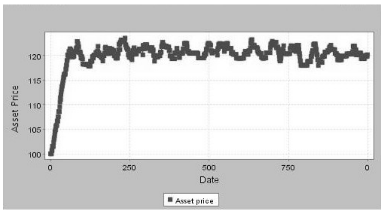
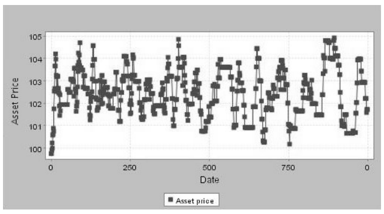


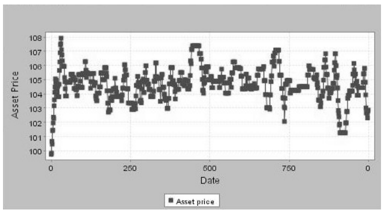

Figure 5: Speculative behaviour with heterogeneous risk thresholds ($R_i \propto U[0.4; 0.8]$)

### 4.4 Sensitivity to the Greater Fool Factor

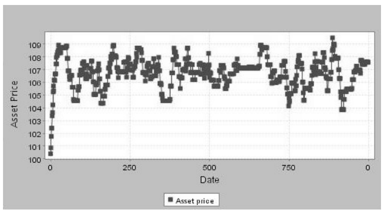
A third experiment investigates the impact of the Fool Factor $\alpha$. As shown in Fig. 6, the average exchange price increases with $\alpha$. A posteriori, it can be explained as the overall number of buyers, everything else being equal, increases with $\alpha$.



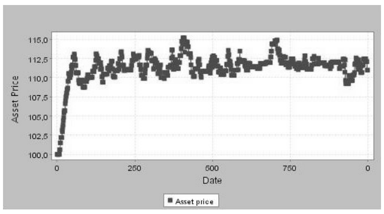

(a) $\alpha = 1.$ ; $Avg. \approx 103$




(b) $\alpha = 1.05$ ; $Avg. \approx 105$




(c) $\alpha = 1.1$ ; $Avg. \approx 107$




(d) $\alpha = 1.2$ ; $Avg. \approx 111$

Figure 6: Influence of the Greater Fool Factor: the exchange price increases with $\alpha$.

### 4.5 Speculative Bubbles

A last setting is concerned with the modelling of speculative bubbles, displaying a price explosion followed by a steep crash. The experiments investigate the impact of two factors, namely the weight of the price slope ($w_i$) in the risk function, and the pricing distribution in panic mode.

By increasing $w_i$ from 3 to 5 and lowering the offers in panic mode ($value \propto U[.95p(t-1), p(t-1)]$ instead of $value \propto U[.99p(t-1), 1.01p(t-1)]$ as in both other modes), the market behaviour shows speculative bubbles (See Fig. 7 for a typical behaviour of the price curve in such a situation).

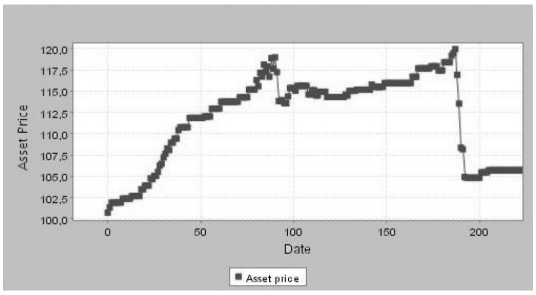



Figure 7: A speculative bubble: $R_i \propto U_{[0.4;0.8]}$, $w = -5$ and asymmetric pricing in panic mode

## 5 Discussion and Perspectives

The artificial market presented in this paper is based on stochastic-zero-intelligence agents. Each agent selects an exuberant, comfortable or panicky strategy depending on the comparison of its risk estimate with its risk thresholds.

Interestingly enough, this 4-parameter model displays a variety of market behaviours. First, it results in an efficient market behaviour as long as it involves homogeneous agents: the exchange price converges toward the fundamental value and quickly adapts to changes in this fundamental value.

As the agent risk thresholds become heterogeneous (following a uniform distribution centered on .6), the market forgets about the fundamental value and tends to overestimate the asset value.

Finally, speculative bubbles are observed in conjunction with i) heterogeneous agents; ii) asymmetrical pricing behaviour in panic mode; iii) a great sensitivity to recent trends in price history.

This work opens up several perspectives for further research beyond more systematic experimentations of the model. First, it is guessed that speculative bubbles are observed within a narrow region in the parameter space;

the characterization of this region might lead to refining the agent model and the critical behavioural parameters.

Another perspective, concerned with the agent rewards, aims at the best regions in the agent parameter distribution. Along this perspective, it might be interesting to determine "zero-loss regulatory strategies", in charge of price regulation and ensuring a minimal financial loss.

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