An Artificial Stock Market with Interactions Network and Mimetic Agents

Sadek Benhammada[1], Frédéric Amblard[2] and Salim Chikhi[1]

[1]MISC Laboratory, University of Constantine 2, Constantine, Algeria
[2]UMR 5505 CNRS-IRIT, Université Toulouse 1 Capitole, Toulouse, France
benhammada@yahoo.fr, frederic.amblard@ut-capitole.fr, chikhi@umc.edu.dz

Abstract: Agent-based artificial stock markets attracted much attention over the last years, and many models have been proposed. However, among them, few models take into account the social interactions and mimicking behaviour of traders, while the economic literature describes investors on financial markets as influenced by decisions of their peers and explains that this mimicking behaviour has a decisive impact on price dynamics and market stability. In this paper we propose a continuous double auction model of financial market, populated by heterogeneous traders who interact through a social network of influence. Traders use different investment strategies, namely: 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. An experimental design is performed to show the feasibility and utility of the proposed model.

1 INTRODUCTION

In financial market, traders can be influenced by decisions of their peers. This phenomenon is called herd (or mimetic) behaviour, and attracted much attention for several decades. The reason for this interest is that mimicking behaviour has a decisive impact on price dynamics, and it might offer an explanation of excessive volatility and creation of bubbles (e.g. (Manahov, 2013) and (Chang, 2014)).

In the literature we distinguish three main reasons for mimicking behaviour to occur in financial markets, i.e., when a decision of an investor can be influenced by observing the actions of other investors: (1) incomplete information, (2) concern for reputation and (3) compensation structures (Bikhchandani, 2000).

The information based models, such as in (Banerjee, 1992) and (Scharfstein, 1990 assume that individuals have private (but imperfect) information about the course of action, they can also observe each other's actions but not the private information or signals that each player receives. Investors may consider optimal to follow the behaviour of the preceding individual disregarding his own information. Other models such as in (Chang, 2014),

are based on herding caused by compensation. In fact, performance evaluation of a fund manager that invests for his employers is often based on relative (not absolute) performance, i.e., his compensation increases with his own performance, and decreases if he produces a performance below than other fund managers. This leads him to conform his investment decisions to those of other professionals, more than he would if he was acting on his own account. Also, reputational concerns of fund managers can also provide a motivation to be mimetic. Indeed, when managers take the same decisions, even if the result of the investment is poor, observers may conclude that there is a high probability that managers are of good quality and that the bad result is accidental. Thus, many proposed models are based on reputation concerns (Scharfstein, 1990).

However, it is difficult to test those theoretical models directly (Manahov, 2013), because it is difficult to access at a time t to private information of traders, their investment strategies and interactions among them. Therefore, it is difficult to determine whether traders make similar decisions as they neglect their own information and imitate others, or because they have access to the same information they use to make their decisions.

To overcome this problem, we can use artificial stock markets (ASM) which are computer models of real stock markets; they are based on modelling market actors by agents, and supposed have the essential properties of real financial markets with the aim of reproducing analyse or understand the dynamics of stock markets, and this by computing experiences (Derveeuw, 2007). In literature, there is a little work that uses ASMs to study the phenomenon of mimicking behaviour on financial markets. In (Manahov, 2013), we propose the study of herd behaviour through the use of an artificial financial market, where the market is populated by agents who are with learning behaviour represented by the genetic programming algorithm. Therefore, as in real markets, authors use statistical measures of price series generated by the experiments to quantify mimicking behaviour on the market. This limits the ability of the model to study the phenomenon.

In this paper we propose a continuous double auction ASM with heterogeneous traders. The proposed ASM is populated by heterogeneous traders which are bound by interaction network. Traders use different investment strategies, among them, the mimetic traders which are able to imitate the decisions of their successors in the interactions network. To test the model we perform a series of experiments, and we analyse their results.

This paper is organized as follows. Section 2 presents a description of the proposed model, in section 3 we perform a series of experiments and we discuss the results. Finally, Section 4 concludes and outlines open research directions.

2 STRUCTURE OF THE ASM

In this section we introduce a continuous double auction model with heterogeneous traders. The proposed ASM has four main components (see Figure 1): (i) Market which allows buyers and sellers to exchange assets; (ii) Traders who exchange assets in the market; (iii) External-world that is the source of information used by traders to estimate the fundamental value of assets; and (iv) social network that allows traders to interact and learn about the decisions of their predecessors.

2.1 The Market

The role of Market is to receive and process orders placed by traders. An order submitted by one trader is described by a direction (buy or sell), a quantity of assets to buy or sell, and a quoted price. The quoted price of a buy (sell) order is the maximum (minimum) limit price above (under) which the order should not be executed. Unexecuted orders are placed in the order book. The order book is described by two lists, the list of buy orders, and the list of sell orders. The list of buy orders is arranged in decreasing order of prices, while the list of sell orders is arranged in increasing order. If a submitted order finds a matching order of the opposite side in the book, a trade is generated. When a trade is generated, the Market deletes satisfied orders from the order book, an orders can be satisfied completely or partially (depending on quantity), if order is satisfied partially, the unsatisfied order part is replaced in the book.
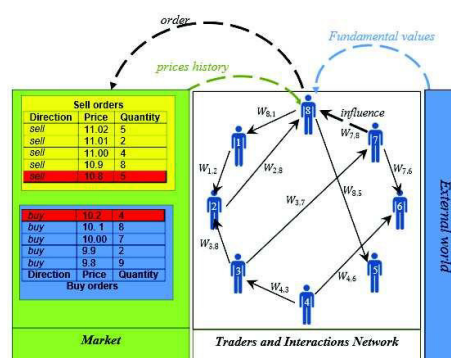

Figure 1: The structure of an artificial stock market.

2.2 External World

The fundamental value of the asset is the expected discounted sum of its future dividends. It represents the true value of asset. To estimate it, analysts use information of external world, such as balance sheet of company and overall state of the economy.

The role of External world is to generate the signal representing the fundamental value of asset that will be received by traders with an error margin. We will use two jump processes to simulate fundamental values. To generate fundamental value without trend, we use the following process:

$$Fv(t + 1) = Fv(t) + \omega_t \qquad (1)$$

Where $\omega_t \backsim \mathcal{N}(0, \sigma)$ is a white noise from a normal distribution with mean 0 and variance $\sigma^2 = 1$.

To have an uptrend of prices over a period, and stimulate speculative behaviour of hybrid agents (see section 3.4), we will generate a fundamental value with increasing trend during the first n transactions, and without trend (equation 1) during the rest of simulation. To generate a fundamental

value with increasing trend we use the following process:

$$Fv(t+1) = Fv(t) + b + \omega_t \qquad (2)$$

$b > 0$ is a positive constant.

2.3 Interactions Network

To study the mimicking behaviour, we need to model the social network of interactions of traders in the market, through which, they can access to actions of each other, and eventually imitate them.

Thus, the interactions network is represented by a directed graph, where the nodes represent the traders, while edges represent the interactions among them. The interactions are assumed unidirectional (i.e., agent j-th influences agent i-th, but the reverse isn't necessarily correct). Interactions are characterized by a weight $w_{i,j}$, assumed a positive real number, and it represents the degree of confidence of trader i, in the decisions of trader j.

To produce a realistic social network, we use the "small-world" model of Watts-and-Strogatz (Watts, 1998). Creating a Watts-Strogatz network is carried out at two steps:

(1) Create a ring network with N nodes; each node is connected to the same number k of nearest neighbours in the two sides.

(2) Remove each edge with uniform probability p and rewire it to one of nodes that are chosen uniformly at random.

2.4 Traders

The market is populated by traders who exchange (buy and sell) assets. According to the used strategy to make decision, we use different types of traders:

2.4.1 Noise Traders

Noise traders represent traders who don't have sufficient access to information and/ or don't have sufficient competence to use information in decision making. So, he makes a decision to submit a buy order, a sell order or wait with corresponding probabilities P_{buy}, P_{sell} and P_{wait}.

2.4.2 Fundamentalist Traders

Fundamentalists estimate the fundamental value of the asset with a small error margin, and use it to make decisions. Thus, to make a decision, a fundamental trader i estimates a fundamental value $fv_i(t)$ and compares it with current price in Market $p(t)$. If $p(t) < fv_i(t)$, trader i considers

that assets are undervalued, and so decides to submit a buy order. If $p(t) > fv_i(t)$, he consider that asset is overestimated and he place a sell order.

2.4.3 Hybrid Traders

Hybrid traders are initially fundamentalists, but can switch to the speculative behaviour when they detect a sufficient uptrend in prices history and sufficient liquidity.

A hybrid trader i stand initially in fundamental strategy. It has a desire $D_i(t)$ to become speculative, initialized by InitD$_i$. It continuously observes prices trend using moving average (equation 3) (Martinez, 2009) and market liquidity with Effective Spread (ES$_i$(t)) (Bessembinder, 2009) (equation 4).

$$MA(L,t) = \frac{p(t) - \left(\frac{1}{L}\sum_{i=1}^{L} p(t-i)\right)}{\frac{1}{L}\sum_{i=1}^{L} p(t-i)} \qquad (3)$$

t is the current time and L is a period length.

$$ES_i(t) = \frac{p(t) - fv_i(t)}{fv_i(t)} \qquad (4)$$

$p(t)$ is the last price of asset at time t, $fv_i(t)$ is the estimated fundamental value by trader i at time t.

Once it observes a sufficient uptrend $(MA(L,t) > thMA_i)$ associated with sufficient liquidity $(ES_i(t) < thES_i)$, it can switch to technical behaviour with a probability proportional to its desire $D_i(t)$. If it persists in fundamentalist behavior, it increases his desire of speculation $D_i(t+1)$ as follows:

$$D_i(t+1) = D_i(t) + \rho_i \qquad (5)$$

When trader i adopts technical (speculative) strategy, he continuously observes prices trend and market liquidity. If price tends to decline $(MA(L,t) < -thMA_i)$ or market liquidity is insufficient $(ES_i(t) \geq thES_i)$, it return to the fundamental strategy.

2.4.4 Mimetic Traders

Mimetic traders represent traders who consider that their own information is incomplete to making decision, and take their decision by imitating others.

A mimetic trader i can access to actions of its successors in the interaction network (see section 3.3), thus, to make a decision, mimetic trader i imitates the last decision of one of its successor's j. Imitated successor j is chosen using roulette-wheel selection, i.e., proportionally to the weights of interactions $w_{i,j}$ which represents the degree of confidence of trader i in decisions of his successor j

(see Figure 2.). Mimetic trader has a learning mechanism for updating weights of its interactions (see Figure 3); the aim is to foster imitation of predecessors who are able to make correct decisions based on the analysis of the price trend. Thus, each mimetic trader i keeps the list $Imitated_i$ of imitated decisions, to be able to evaluate them later, and thus updates the weights of its interactions with the imitated successors according to this evaluation.

Algorithm Make a decision
   Parameters:
    $LastDecision_i$: The last decision tacked by trader i.
    $LastDecision_j$: The last decision tacked by trader j.
    $W_{i,j}$: Weight of interaction between mimic trader i and imitated successor j.
    $Strategy_i$: Strategy of trader i.
    $Strategy_j$: Strategy of trader j.
   Output:
    Decision (*buy, sell*)
   Select one successor j of trader i using roulette-wheel, proportionate to the weights of interactions $W_{i,j}$.
   $Strategy_i = Strategy_j$
   $LastDecision_i = LastDecision_j$
   if $(LastDecision_j = buy)$
     return *buy order*
   else $(LastDecision_j = sell)$
     return *sell order*
   end if

Figure 2: Make a decision algorithm of mimetic trader.

An imitated decision can be described as a triplet $d = (type_d, t_d, succ_d)$, while: $type_d$ is the type of imitated decision (*buy* or *sell*), t_d the time when decision d is imitated, and $succ_d$ the imitated successor. To update the weights of interactions with imitated successors at time t, a mimetic trader i filter a list of evaluable decisions $Evaluables_i(t)$. An imitated decision is considered evaluable if the time since its imitation is greater than or equal to a duration Δ_i:

$$Evaluables_i(t) = \{d \in Imitated_i(t) \mid t - t_d \geq \Delta_i\}$$

Mimetic trader i retains for each interaction with trader j a value $AbsW_{i,j}$ that we call absolute weight; $AbsW_{i,j}$ is used to calculate the interaction weight $W_{i,j}$ with a sigmoid function as follows:

$$W_{i,j} = \frac{w_{max}}{1 + ae^{-r*AbsW_{i,j}}} \quad (6)$$

w_{max} a, r are positive real.
Sigmoid function aims to obtain a weight with a quite slow slope in the beginning, followed by acceleration, and finally slows down and approaches (w_{max}).

Algorithm Update Interactions Weights
   Parameters:
    $Evaluables_i(t)$: List of evaluable decisions
    $W_{i,succ_d}$: Weight of interaction with imitated $succ_d$
    $AbsW_{i,succ_d}$: Absolut weight of interaction between mimic trader and imitated successor $succ_d$
    γ: Rate used to update $W_{i,succ_d}$.
    ε: Threshold used to determine if price has significantly increased or decreased.
   $m \leftarrow (p(t) - p(t - \Delta_i))/p(t - \Delta_i)$
   for each $d \in Evaluables_i(t)$:
    if $(type_d = buy)$
      if $(m > \varepsilon)$: $AbsW_{i,succ_d} \leftarrow AbsW_{i,succ_d} + |m|$;
      else : $AbsW_{i,succ_d} \leftarrow AbsW_{i,succ_d} - |m|$;
    else /* $(type_d = sell)$*/
      if $(m < -\varepsilon)$: $AbsW_{i,succ_d} \leftarrow AbsW_{i,succ_d} + |m|$;
      else: $AbsW_{i,succ_d} \leftarrow AbsW_{i,succ_d} - |m|$;
    $W_{i,succ_d} = \dfrac{k}{1 + ae^{-r*AbsW_{i,succ_d}}}$
    delete decision d from $Evaluables_i(t)$
   end for

Figure 3: Algorithm for updating interactions weights.

3 EXPERIMENTS & DISCUSSION

We designed a model to study mimicking behaviour in stock markets. As mentioned in the introduction, herd behaviour has an important effect on asset prices in stock markets; it is considered as the first explanation of the phenomenon of speculative bubble formation ((Orléan, 1989) and (Chang, 2014)). However, does the model give realistic prices dynamics? Also, are the mimetic traders designed able to cause mimetic contagion, and reproduce a realistic speculative bubble such as indicated in theoretical assumptions?

3.1 Metrics and Tools

To test the model, we will perform experiments and analyse the output price series, and the evolution of the state of traders and interactions network. In order to verify whether prices dynamics of our model are realists, we analyse statistic properties (mean, median, minimum, maximum, kurtosis and skewness) and we compare it with them of real price series. To see the formation of realistic bubbles, we observe measures introduced in experimental economics literature to analyse bubbles magnitude, which are the following:
(1) *Relative Deviation (RD)*, is the average deviation of prices from fundamental value relative to the average fundamental value (Stöckl, 2010).

$$RD = \frac{1}{T}\sum_{t=1}^{T}\frac{P(t) - Fv(t)}{FV} \quad (7)$$

(2) *Boom Duration*, which equals the greatest number of consecutive periods when prices increase relatively to fundamental value (Füllbrunn, 2012).

(3) *Bust Duration* which is the greatest number of consecutive periods when prices decrease relatively to fundamental value (Füllbrunn, 2012).

(4) *Positive Deviation (PD)*, a deviation of the price from the fundamental value if prices are above (below) fundamental value (Füllbrunn, 2012).

$$PD = \sum_{P(t)>FV(t)} |P(t) - Fv(t)| \qquad (8)$$

(5) *Negative Deviation (ND)*, defined as deviation of the price from the fundamental value if prices are below fundamental value (Füllbrunn, 2012).

$$ND = \sum_{P(t)<FV(t)} |P(t) - Fv(t)| \qquad (9)$$

A bubble is characterized as (1) the positive Relative Deviation (*RD* is not below or at zero), (2) long Boom Duration and short Burst Duration (*Boom> Burst*), and (3) high Positive Deviation and low Negative Deviation (*PD>ND*) (Füllbrunn, 2012). Thus, to verify these properties, we will test the corresponding null hypothesis (i.e. (1) $RD \leq 0$, (2) $Boom \leq Burst$, and (3) $PD \leq ND$).

Also, given that the decisions of a mimetic trader are imitations of their successors, and that the choice of successor to imitate depends on the weights of its interactions with him (see Figure 2) thus, to be able to measure the influence of each type of traders on decisions of mimetic traders, we measure the average of interactions weights with each type of traders as follow:

Let $w_1^T, w_2^T, \ldots, w_x^T$ weights of interactions where: (1) predecessor is mimetic trader, (2) successor is a trader of type $\mathcal{T}$ which can be *Noise*, *Fundamentalist*, *Hybrid*, or *Mimic*, i.e. $\mathcal{T} \in \{N, F, H, M\}$. x is the traders number of the type $\mathcal{T}$.

$$\overline{W_M^{\mathcal{T}}} = \frac{1}{x} \sum_{a=1}^{x} w_a^{\mathcal{T}} \qquad (10)$$

Thus, there will be four weight averages: $\overline{W_M^N}$, $\overline{W_M^F}$, $\overline{W_M^H}$ and $\overline{W_M^M}$.

Also, to better understand prices dynamic and trader's behaviour, we will interest to the strategies used by traders to make a decisions on the market. For fundamentalist and noise traders, the strategy is obviously fundamentalist and noise respectively. For hybrid traders, strategy is the one used to take the last decision (technical or fundamentalist). For mimetic trader, strategy is the one used by imitated trader to make imitated decision (see Figure 2).

Finally, we will use social networking visualization tools to visualize the evolution of the interactions of traders and their strategies.

3.2 Experimental Settings

Table 1 shows values for general model parameters of all performed experiments. Given the large number of model parameters, we content with relate only general parameters of the experiments, namely general parameters of market which have the same values in all experiments, and the same for the parameters of generated fundamental values. What will change in performed experiments are the proportions of different types of traders, except the noise traders that are set at 10% in all experiments, and whose role is to ensure market liquidity (Kobayashi, 2007). First, we test model with fundamentalists trading (EXP.1), after we will introduce hybrid traders (EXP.2). Finally, we introduce the mimetic traders in EXP.3. The aim is to show that mimetic traders are able to cause a mimetic contagion of speculative behaviour and a deviation of prices from the fundamental value, in the same way as hybrid traders.

Table 1: Experimental design.

		EXP.1	EXP.2	EXP.3
General parameters of Market	Nbr. of transactions	2000	2000	2000
	Number of traders	500	500	500
	Open price	1000	1000	1000
Proportions of traders	Noise traders	10%	10%	10%
	Fundamental traders	90%	10%	10%
	Hybrid traders	0%	80%	10%
	Mimetic traders	0%	0%	70%
Parameters of generated fundamental values	Initial *FV*	1000	1000	1000
	b (eq. 2)	0,5	0,5	0,5
	n (section 2.2)	500	500	500

3.3 Analyse of Results

First, we will observe the statistical properties of the experiments and compared with two real price series (FTSE100 index and Barclays bank's (Martinez, 2009)). Table 2 shows that price series generated by our model have statistical properties that are close to the real series. For example, it has been found in real financial market, that prices series exhibit a kurtosis larger than three, which indicate a leptokurtic distribution of return. This phenomenon is known as fat tails (Martinez, 2009). Thus, as real series, the series generated by experiments have a kurtosis larger than three, and so exhibit a phenomenon of fat tails.

After having presented the statistical properties of performed experiments, now we will analyse and discuss results of each experiment regarding the dynamics of prices and its relationship with the behaviour of traders.

Table 2: Statistical properties of log return in performed experiments.

	Mean	Median	Min.	Max.	Kurtosis	Skewness
FTSE100	-0,00003	0	-0,059	0,059	5,138	-0,130
Barclays	0,00020	0	-0,090	0,094	4,626	0,113
EXP.1	0,00017	0	-0,067	0,078	5,208	0,219
EXP.2	0,0003	0	-0,035	0,041	9,509	0,586
EXP.3	0,00019	0	-0,035	0,045	4,133	0,460

3.3.1 Fundamental Trading

In order to analyse prices dynamics with fundamentalist traders, we perform EXP.1, with population composed from 90% of fundamentalists and 10% of noises (see Table 1). We can see in Figure 4 that prices fluctuate around the fundamental value. In Table 3 $RD=0.001$ is close to 0, also, the test doesn't reject a null hypothesis that $RD \leq 0$, which confirm that prices follow closely fundamental value (Füllbrunn, 2012). In fact, fundamentalist traders which represent the majority of traders submit orders with prices close to fundamental value, and thus prevent the deviation of prices from the fundamental.
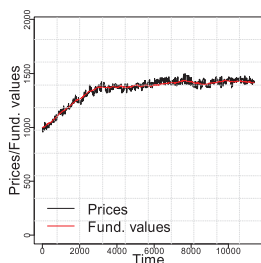

Figure 4: Evolution of prices and FV in EXP.1.

3.3.2 Introduction of Hybrid Traders

We will observe price dynamics in the presence of hybrids that can switch between fundamentalist and speculative strategies. Are they able to cause a deviation of prices and the formation of bubble by their speculative behaviour as stated in the literature?

In EXP.2 when population of traders is composed from 80% of hybrids and 10% of fundamentalists, we can see in Figure 5(a) the deviation of prices from fundamental value that takes the form of a bubble followed by a crash, also,

the three null hypotheses was rejected, which indicates a deviation of prices from fundamental value with the magnitude of a bubble. In fact $RD=0,194$ is positive (see Table 3), which indicate that asset is overvalued. Also, *Boom* is higher than *Burst* and both durations are significantly higher compared to the number of periods (150). $ND=2k$ isn't significant regarding $PD=1043k$, which confirms a positive deviation of prices from fundamental values. A formation of bubble in EXP.2 can explain by the behaviour of hybrid traders which represent a majority in population. In fact, the switching of hybrid traders to technical strategy (see Figure 5(b)) led to a boom phase when prices increase and deviate from fundamental value, then return to the fundamentalist behaviour led to a burst phase when prices decrease and remain close to fundamental values.
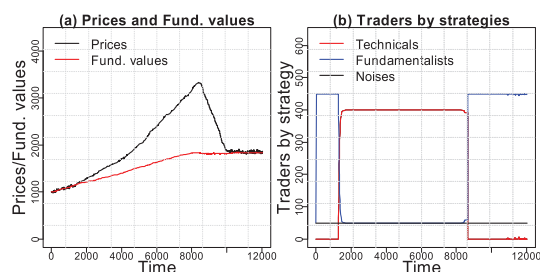

Figure 5: Evolution of prices and the number of traders by strategies in EXP.2.

3.3.3 Introduction of Mimetic Traders

We will observe price dynamics in the presence of mimetic traders (section 2.4.4), to see if their mimetism will lead to diffusion of speculative behaviour in the market, and formation of bubbles, such as reported in the literature (e.g. (Orléan, 1989) and (Chang, 2014)).

In EXP.3 when population of traders is composed from 70% of mimetic traders and 10% of noises, fundamentalists and hybrid traders. We can see in Table 3 that $RD=0,123$ is significantly positive and the same for *Boom* and *Burst* duration, which indicates a significant deviation of price from fundamental value. The test reject the three null hypothesis which indicate that a deviation of prices from fundamental values has the magnitude of speculative bubble (Figure 6(a)) such as in EXP.2 when population is composed from 80% of hybrids.
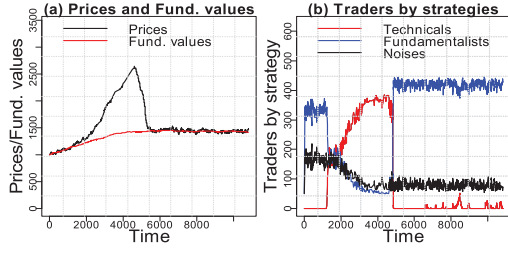
Figure: 6 Evolution of prices and the number of traders by strategies in EXP.3.

Figure 6 (b) represents the number of traders for each strategy as function of time. We can see that the majority of trader's deviate to speculative strategy during the period when prices increase, in fact, 10% of hybrid traders switch to speculative behaviour due to the uptrend in prices, and then the vast majority of mimetic imitate speculative decisions of hybrids, and thus become speculators as can be seen in Figure 7 (a) and Figure 7 (b). Figure 7 (c) shows that the weights average of mimetic interactions with hybrids $\overline{W_M^H}$ and mimetic $\overline{W_M^M}$ are largely greater than those of fundamentalists $\overline{W_M^F}$ and noises $\overline{W_M^N}$. This indicates that mimetic traders tend to imitate hybrids or other mimetic traders.
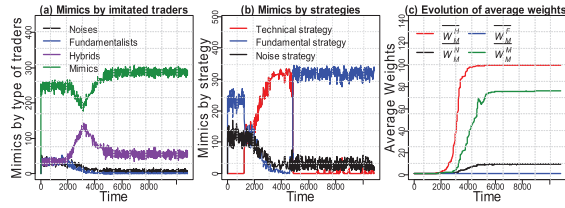

Figure 7: Evolution of mimetic traders by (a) trader types (b) strategies, and (c) weight averages of interactions with mimetic traders in EXP.3.

In other word, speculative behaviour first contaminates mimetic traders that interact with hybrid traders, and then gradually contaminates other mimetic traders which don't interact directly with the hybrids. This corresponds exactly to the mimetic contagion, which causes the phenomenon of the bubble as described in the literature (e.g. (Orléan, 1989) and (Chang, 2014)).

Finally, for better understand the behaviour of traders, and interactions between them, we have used Gephi tool (Bastian, 2009) to visualize a traders, their types and investment strategies, and their interactions in different periods of simulation.

Figure 8 present visualizations of traders and their interactions in 4 key periods of experiments EXP.3. A stickman represents a trader; colours represent their investment strategies. To visualize

Table 3: Means of observed bubble measures, and test of null hypothesis significance in performed experiments. (*) indicates that null hypothesis is rejected.

	EXP.1	EXP.2	EXP.3
Boom	2	41	30
Burst	2	21	12
RD	0,001	0,194	0,123
PD	20 k	1043 k	471 k
ND	17 k	2 k	7 k
H0 : $RD \leq 0$	*p>0,05*	*p<0,05**	*p<0,05**
H0 : *Boom ≤ Burst*	*p>0,05*	*p<0,05**	*p<0,05**
H0 : *PD ≤ ND*	*p>0,05*	*p<0,05**	*p<0,05**

In the beginning (time 0)	After 300 transactions (time 1879)
After 500 transactions (time 4219)	After 800 transactions (time 5041)

Noise trader — Mimetic with noise strategy
Fundamentalist trader — Mimetic with fundamental strategy
Hybrid with fundamental strategy — Mimetic without strategy
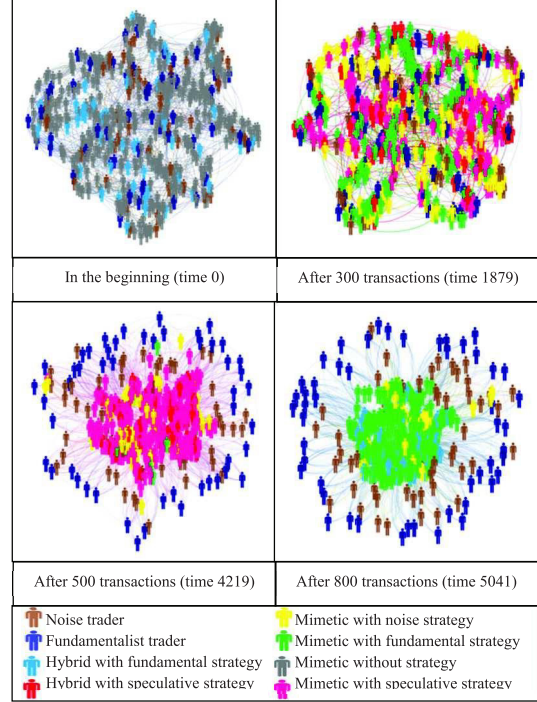Hybrid with speculative strategy — Mimetic with speculative strategy

Figure 8: Visualization of traders and their interactions network in EXP.3.

interactions network, we applied the Force Atlas algorithm, which pulls together nodes connected with strong interactions, while repelling away all other nodes. This provides a much more readable representation of the graph.

Before the start of the simulation, we can see that the market is populated by a majority of mimics (grey stickman), with 10% noises (brown stickman), 10% of fundamentalists (blue stickman), and 10% of hybrids, initially use fundamentalist strategy (sky blue stickman).

After 300 transactions, all hybrid traders chose speculative strategy (in red), when mimetic traders are divided between fundamental strategy (in green), speculative strategy (in violet) and noise decision (in yellow). They haven't preference for a particular strategy.

After 500 transactions, the mimetic approach each other, and with hybrid traders, indicating a high weights of interactions between them. Thus, the majority of mimetic traders imitate speculative decisions of hybrids, which leads to the formation of a bubble.

After 800 transactions, mimetic traders always have strong interactions between them and with hybrid traders, the majority of mimetic traders switch to fundamentalist behaviour with hybrids, which causes the crash.

4 CONCLUSIONS

In this paper we introduced an agent based model of double auction market with heterogeneous traders and a social network of interactions. The market is populated by different types of traders, namely, (1) noise traders which represent misinformed traders in the market, (2) fundamental traders which make their decisions based on their estimate of the fundamental value, (3) hybrids which represent traders able to switch to speculative behaviour when they detect an uptrend in prices, and finally, (4) mimetic traders which take decisions by imitating their successors in interactions network.

To test the model, we conducted a series of experiments and compared statistical properties of generated prices series with those of real market, and also, we tested theoretical assumptions which consider mimetic traders as the first explanation of the phenomena of speculative bubble. Experiments have shown that prices series generated have statistic properties close to those of real prices series. Also, results of experiments support theoretical assumption concerning the important role of mimicking behaviour as an explanation of excess volatility and bubbles formation. In fact, when market is populated by a majority of mimetic traders, they choose to imitate speculative decisions, resulting in price volatility and the formation of a bubble.

The proposed model provides access to all the information concerning the decisions of traders, their strategies and their interactions; this will have to provide a more efficient way to study the mimicking behaviour and its role on financial markets.

Regarding the perspective, we will improve the model through the development of agents that better simulate the behaviour of traders in real markets.

REFERENCES

Bikhchandani, S., & Sharma, S. (2000). Herd behaviour in financial markets. *IMF Economic Review*, *47*(3), 279-310.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, 797-817.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behaviour and investment. *The American Economic Review*, 465-479.

Derveeuw, J., Beaufils, B., Mathieu, P., & Brandouy, O. (2007). Testing double auction as a component within a generic market model architecture. In *Artificial Markets Modeling* (pp. 47-61). Springer Berlin Heidelberg.

Orléan, A. (1989). Mimetic contagion and speculative bubbles. *Theory and Decision*, *27*(1-2), 63-92.

Martinez-Jaramillo, S., & Tsang, E. P. (2009). An heterogeneous, endogenous and coevolutionary GP-based financial market. *IEEE Transactions on Evolutionary Computation*, *13*(1), 33-55.

Bessembinder, H., & Venkataraman, K. (2009). Bid-ask spreads: Measuring trade execution costs in financial markets. *Encyclopedia of Quantitative Finance*.

Füllbrunn, S., & Neugebauer, T. (2012). Margin Trading Bans in Experimental Asset Markets. *Jena Economic Research Paper*, *58*.

Stöckl, T., Huber, J., & Kirchler, M. (2010). Bubble measures in experimental asset markets. *Experimental Economics*, *13*(3), 284-298.

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: an open source software for exploring and manipulating networks. *ICWSM*, *8*, 361-362.

Chang, S. K. (2014). Herd behavior, bubbles and social interactions in financial markets. *Studies in Nonlinear Dynamics and Econometrics*, *18*(1), 89-101.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *nature*, *393*(6684), 440-442.

Kobayashi, S., & Hashimoto, T. (2007). Analysis of Random Agents for Improving Market Liquidity Using Artificial Stock Market. In *Proceedings of The Fourth Conference of The European Social Simulation Association (ESSA 4th'07)* (pp. 315-317).

Manahov, V., & Hudson, R. (2013). Herd behaviour experimental testing in laboratory artificial stock market settings. Behavioural foundations of stylised facts of financial returns. *Physica A: Statistical Mechanics and its Applications*, *392*(19), 4351-4372.