Looking for the self-fulfilling prophecy effect in a double auction artificial stock market

Abstract—**This work proposes a double auction artificial stock market based on the Santa Fe market structure. Our market tries to shed light on some facts that usually arise in real stock markets, specially the creation of technical figures in price series. The origin of these figures is believed to be caused by the self-fulfilling prophecy effect, which will be investigated with the proposed market.**

I. Introduction

The main purpose of the agent-based simulation of an artificial stock market (ASM) is to reproduce, in a controlled environment, some properties of real stock markets. In that way, ASMs are a suitable tool to analyze and understand market dynamics. See [1] for a comprehensive review of the topic.

Many market models has been developed in order to reproduced those properties, like Genoa Stock Market [2], [3], $-Game [4], or the Santa Fe Institute Stock Market (SFM), developed by LeBaron and his coauthors since the early nineties and analyzed in depth in [5]. Most of them are able to reproduce several well-known market properties -called stylized facts,- while each market has his own special microstructure. However, in the time series of prices that emerges in ASMs it is difficult to find some of the typical behaviors that appear in real-life price time series, for example, the bid-ask bouncing or the sideways movement within the support and resistance lines.

These behaviors, which are usually know as technical patterns, cannot be explained from the fundamental analysis perspective. Despite this fact, they are used by many investors and also by chief dealers, as is reported in [6]. The reality is that patterns such as trends, channels, resistances and supports can be spotted in stock charts. A possible explanation to these phenomena is the self-fulfilling prophecy effect [7]. As many people look for similar technical patterns in the stock markets and place their orders according to them, the patterns finally emerge as a result of this collective belief. This belief is reinforced when the stock price behave as expected, because technical traders feel confident with their chartist strategy and technical analysis is considered as a useful tool.

Technical analysts, also known as chartist investors, base their expectations in historical price patterns that are expected to appear again at some future point. They try to predict future extreme prices in order to buy assets when the value is under those limits, and sell them when the price is close to a bounce zone. Moreover, technical traders usually follow price trends. A common example is the use of the moving averages crosses to set their trading strategies. This method provides buy and sell signals when a short run moving average crosses a long run moving average price.

Chartism is one of the two main investment approaches that can be usually found in stock markets [8]. The other one is fundamental trading, where investors base their investments upon future price expectations based on fundamental and economic factors, such as future dividend expectations, macroeconomic data and growth prospects. Nowadays, investors and chief dealers combine both technical and fundamental information [6]. Frankel and Froot in [9] showed that both approaches affected the US dollar exchange rate in the eighties. They associated the long-term expectations, which are stabilizing, with fundamentalists, and the shorter term forecasts, which seem to have a destabilizing nature, with the chartist expectations. As a result, many people used weighted averages of the chartist and fundamentalist forecasts in formulating their expectations for the value of the dollar at a given future date, with weights depending on how far the date is.

This article proposes an ASM based on the SFM structure that exhibits technical figures and that reproduce the self-fulfilling prophecy effect. The proposed ASM modifies some important features of the SFM with the aim of being more realistic and reproducing stylized facts. The most relevant changes are introduced in the next section.

II. Description of the double auction artificial stock market proposed

The SFM [10], [11] consists of a small number (typically 25) of artificially-intelligent agents that each period choose between investing in a stock and leaving their money invested in a fixed interest rate asset. The stock pays a stochastic dividend and has a price which fluctuates according to agent demand. The agents make their investment decisions by attempting to forecast the future return on the stock with the help of a set of forecast rules that are triggered when they match certain states of the market. Each rule map into a set of parameters that are used to yield a forecast for the future price and dividend using the rational expectations equilibrium theory. The forecast is converted to the share demand, according to the agent's demand function which follows risk aversion behavior. Agents learn through time because their predictive rules evolve by means of a genetic algorithm.

The SFM shows, amongst other features, the theoretically-predicted rational expectations behavior, with low overall trading volume, uncorrelated price series. However, it is difficult to find realistic market behavior such as high trading volume, time-varying volatility clustering (periods of swings followed by periods of relative calm), bubbles and crashes and market patterns such as supports, resistances, channels, etc. One of the main reasons is that the auction mechanism is not realistic as there is an auctioneer that takes into the account the demand of shares and the fixed supply of shares (25 shares) to set the price that clears the market.

In our ASM, a continuous double auction system is implemented. In continuous double auction markets, agents place buy or sell orders at any time in an asynchronous manner. In this kind of auctions, a public order book lists the bids in descending order and the sell offers in ascending order. When a new order matches with the best waiting order of the opposite type then a trade is made, otherwise the new order remains waiting. Once the transaction is carried out, both orders are removed from the order book. This kind of auction is implemented in stock markets such as NYSE or AMEX. This kind of auction has been already implemented as an ASM [12], [13], [2], [14], where some aspects of market dynamics are successfully explored. As continuous double auction is commonly used in real stock markets, we believe that is the most suitable auction mechanism for an ASM that aims to replicate these markets.

In our market, agents are rationally bounded, , which means that their rationality is limited by the information they have. They make price bids (offers to buy) and/or price asks (offers to sell) subject to a budget constraint and using the information they have about the state of the market. Our market allows agents to place both market-price and fixed-price orders. The ASM does not allow fixed-price orders. However, this kind of orders are used in real-life stock markets. In an artificial market that allows this orders it is possible to observe technical patterns. If a group of traders set fixed-price orders close to a certain price value, then supports or resistances lines may appear in the resulting price time series. Also, cascade effects could emerge behind certain price limits obtained using technical analysis.

In our ASM, agents tune the fixed-price orders using a system of forecasting rules similar to that used in the SFM, but based on support and resistance lines. In doing so, they will fix the price taking into account the support and resistance lines and the length of the trading horizon (it denotes if is a short-, mid- or long-term trade). The mechanism will be described below.

Our market follows the basic structure of the SFM model, but implementing a double auction market. Another noteworthy difference is the number of agents. Instead of the 25 agents used in the SFM, in our market there are 512 agents that will make possible to have enough trade operations in the market and a great variety of behaviors. It is important to remark that our aim is not related with the rational expectations equilibrium theory, but with the study of real-life phenomena such as resistance and support lines. These changes affect not only the auction mechanism but also the equations that determine the wealth and the classifier rules. More details will be given in the next subsections.

A. Agent's trading strategy

As in the SFM, our market has two assets: a risk free bond in infinite supply with constant interest rate ($r = 0.1$) and a risky asset. The price of the risky asset in t, p_t is endogenously determined by the market. The risky asset considered does not pay dividends, in contrast to the SFM's risky asset.

The trading strategy consists of buying (or selling, if the agent goes short) risky assets at the current price of the market and at the same time placing a fixed price stop-profit order. The price of the stop-profit order is determined by taking into account the agent's resistance line (or the agent's support line, if the agent goes short). Both orders are sent at time t_a. In addition, the agent also estimates the price of a stop-loss order using the support line (or the resistance line, if the agent goes short). This order will be placed as a market-price order only if the risky asset reaches the stop-loss price.

As any market-price operation has its corresponding stop-profit order, the total number of stocks M is always available in the market, providing the necessary liquidity to supply the possible demands of other investors. The system restrictions ensure the liquidity of the market and consequently market price orders are executed at the time when they are placed.

In t_a the stop-profit order is booked in its corresponding priority queue of awaiting orders, depending on if the trading agent goes long or short. The agent determines the stop-profit price using a future stock price that is forecasted with the help of a support line (or a resistance line if the investor is going short) that is drawn by the agent using three parameters determined by the activated forecast rule j (more details about the forecast rules are given in the next subsection). The parameters are: the number of local maximum (resp. minimum) points used to draw the resistance (resp. support) lines $a_{i,j}$, the length of the sliding window used to look for the local maxima and minima $b_{i,j}$, and the length of the trading horizon $c_{i,j}$. A support (resp. resistance) line is drew joining at least two minimum (resp. maximum) price values. These parameters allow agents to operate to different time horizons.

If at time $c_{i,j}$ the price of the risky stock has not been matched the agent close its position and cancel the stop-profit order that was previously submitted. This is an interesting feature because, as is reported in [15] not all researchers in the experimental markets literature allow to cancel limit orders.

B. The classifier system

The behavior of the trader is determined by the classifier system they use to set their trade orders. The classifier system consists of a set of rules that are triggered when some market conditions are present. The classifier system implemented that follow our agents is based on the one used in the SFM, which is described in detail in [11].

The agents have to set of rules one for "going long" and other for "going short". The rules of both sets have the same structure, which consists of two parts. The left part of the rule is a string of 30 conditions, where each string position represents a state of the market. The possible values of each position are 1, 0 or $\sharp$. The 1 means that the state have to be

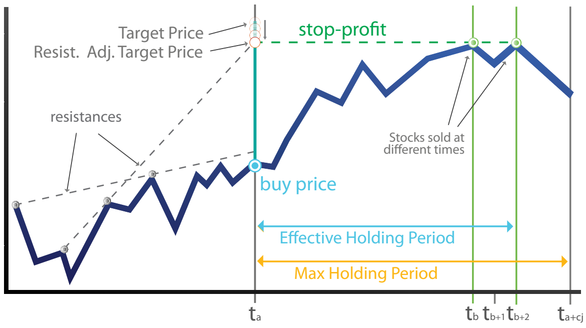

Fig. 1. Time line that illustrates an investment operation made by a trading agent

present, the zero that the state have not to be present while the $\sharp$ is a wildcard that matches either. The right part of the rule consists of three parameters ($a_{i,j}$, $b_{i,j}$ and $c_{i,j}$) that are used to draw the resistance and the support for the trade operation. If the agent is going long, it will use the resistance to set the stop-profit order and the support for the stop-loss order, while if the agent is going short it will do it the other way round. The idea is that each rule matches a state of the system, where the agent invest in the risky stock asset at market price. The position will be held until the asset reaches either the stop-profit or the stop loss prices. If the rule is matched at t_a, the agent expects to reach the stop profit price at $t_a + c_{i,j}$.

The parameters are initially set to random values distributed uniformly. As in the SFM the rules are not static. Each agent is allowed to learn by changing its set of rule. The learning process is implemented by means of a genetic algorithm where the poorly performing rules are substituted by new ones. Rules are selected for rejection and persistence based on a accuracy measure that takes into account both the errors in the price and in the forecast horizon.

C. The state of the agents

When a forecast rule j of agent i is activated in t_a, the agent will forecast the future stock returns for time horizon $t_a + c_{i,j}$, instead of $t_a + 1$ as in the SFM. Once the operation is done, the agent will hold its position until instant $t_a + c_{i,j}$ or until the price of the stock reaches a stop-profit or a stop-loss value at an undetermined time $t_b > t_a$, whatever comes first. In the second case, the operation may not be closed at that undetermined time, which will be denoted as t_b. It happens when there are not enough buy (resp. sell) orders to sell (resp. buy) all the stocks at the stop price in t_b. Figure 1 illustrates the process for the case where the agent goes long.

Once the transaction is completed (i.e. once the ordered stocks have been bought and then sold or viceversa for short positions), the investor's wealth has to be updated. As said before, the transaction is completed either when stocks reach the stop-profit price at t_b or when the holding time period is expired $t_a + c_j$. For the sake of simplicity, we will refer to these periods as t_e. The wealth equation must take into account that the sold of stocks can require more than one period. The number of extra periods will be denoted as f. While agent traders can not execute several operations at the same time, and also can not modify their current trading strategy, wealth value is updated when a trading operation has concluded. Given that, the wealth of agent i in t_{e+f} is

$$W_{t_{e+f},i} = W^{risky}_{t_a \to t_{e+f}} + W^{free}_{t_a \to t_{e+f}} + W^{free}_{t_e \to t_{e+f}}. \quad (1)$$

The equations of these three terms are explained next.

The term $W^{risky}_{t_a \to t_{e+f},i}$ represents the changes from t_a to t_{e+f} in the wealth invested in the risky asset. Its equation is slightly different depending on the way stocks are sold. If they are sold because they reach the stop-profit price, then $t_e = t_b$ is the period when that price is reached and the wealth is

$$W^{risky}_{t_a \to t_{e+f},i} = p_{t_e} \sum_{l=0}^{f} x^{out}_{t_{e+l},i}, \quad (2)$$

where $x^{out}_{t_{e+l},i}$ is the number of stocks sold at time t_{e+l} by agent i and satisfying $\sum_{l=0}^{f} x^{out}_{t_{e+l},i} = x_{t_a,i}$.

On the other hand, if stocks are sold because the maximum holding time ends, which happens at $t_e = t_{a+c_j}$, then all the stocks are sold at that time (which means that $f = 0$). However, it may happen that not all the stocks are sold at the price p_{t_e}. This happens when the demand of the awaiting order does not cover the whole sell. If this is the case, other awaiting orders, possibly with a different price are required. The wealth $W^{risky}_{t_a \to t_{e+f},i}$ in this case is estimated as

$$W^{risky}_{t_a \to t_{e+f},i} = \sum_{l=1}^{v} x^{out}_{t_e,l,i} p_{t_e,l}. \quad (3)$$

As all the stocks are sold at the same price, the price $p_{t_e,l}$ and the stocks number $x^{out}_{t_e,l,i}$ both depend on a parameter $l = 1, ..., v$ that represents the number of awaiting sell order matched.

The second term, $W^{free}_{t_a \to t_{e+f},i}$, represents the evolution of the capital invested in the free risk asset since t_a. It is given by

$$W^{free}_{t_a \to t_{e+f},i} = (1+r)^{t_{b+f}-t_a} \Big(W_{t_a,i} - \sum_{l=1}^{k} p_{t_a,l} x^{in}_{t_a,i,l} \Big), \quad (4)$$

where r is the constant interest rate of the free-risk asset and the pair of values $(p_{t_a,l}, x^{in}_{t_a,i,l})$ represents the awaiting sell order matched at time t with the market price order. It means that $x^{in}_{t_a,i,l}$ stocks have been bought at price $p_{t_a,l}$ with $\sum_{l=1}^{k} x^{in}_{t_a,i,l} = x_{t_a,i}$.

Finally, the term $W^{free*}_{t_e \to t_{e+f},i}$ represents the evolution of the capital of the stocks sold between t_e and t_{e_f}, because during this period this capital is invested in the free risk asset. Thus, the term is only taken into account if $f > 0$. It is given by

$$W^{free*}_{t_e \to t_{e+f},i} = \sum_{l=1}^{f} (1+r)^{t_{b+f}-t_{b+l}} (p_{t_{b+l}} x^{out}_{t_{b+l},i}). \quad (5)$$

In our market as in the SFM, investors use a simply constant relative risk aversion preference for stock demands [16]. When a classifier detects an investment opportunity, the investor agent estimates the asset demands, trying to maximize the wealth utility function $U_{i,t+c_j} = -\exp(-\lambda W_{i,t+c_j})$, where the wealth equation has been described above.

III. Validation of the Model

This paper represents the current state of a work-in-progress. An example of a candlestick time series with the trading volume generated by the ASM is shown in Figure 2. The model is being satisfactorily programmed using Nvidia CUDA technology, which allows to drastically reduce the simulation time. This parallel programming technology also allows to scale the number of agents without increasing the simulation time. Detailed information about trading strategies, agent behavior and evolution, the rule system and auction mechanism will be explained in the subsequent extended paper along with the simulation results and validation.

Regarding validation it will consist of analyzing two issues. First the usual econometric properties, i.e. the *stylized-facts*, that are present in real-life stock market time series such us fat tails and leptokurtic properties in return distributions, excess of kurtosis, no significant autocorrelation and volatility clusters. Second, it will be shown that technical patters, familiar to professional technical analysts, do appear in the time series of the prices as a result of the self-fulfilling prophecy effect.

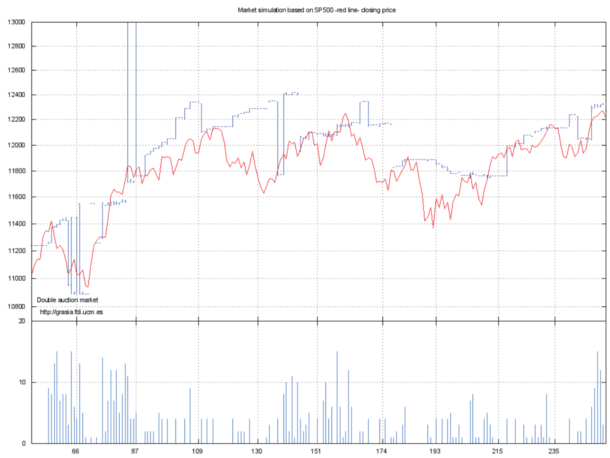

Fig. 2. Preliminary results: synthetic market (blue bars) following SP500 daily closing price (red line) as reference market.

Acknowledgment

The authors acknowledge support from the project *Agent-based Modelling and Simulation of Complex Social Systems (SiCoSSys)*, supported by Spanish Council for Science and Innovation, with grant TIN2008-06464-C03-01. We also thank the support from the *Programa de Creación y Consolidación de Grupos de Investigación UCM-BSCH, GR58/08*

References

[1] B. LeBaron, *The Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics*, ser. Handbooks in Economics Series. Amsterdam: North-Holland, 2006, ch. Agent-based Computational Finance, pp. 1187–1234.

[2] M. Raberto, S. Cincotti, S. M. Focardi, and M. Marchesi, "Agent-based simulation of a financial market," arXiv.org, Quantitative Finance Papers cond-mat/0103600, Mar. 2001. [Online]. Available: http://ideas.repec.org/p/arx/papers/cond-mat-0103600.html

[3] S. Cincotti, S. Focardi, L. Ponta, M. Raberto, and E. Scalas, "The waiting-time distribution of trading activity in a double auction artificial financial market," vol. 567, pp. 239–247, 2006.

[4] J. Andersen and D. Sornette, "The d-game," *European Physics Journal*, vol. 31, no. 1, pp. 141–145, 2003.

[5] N. Ehrentreich, *Agent-Based Modeling: the Santa Fe Institute Artificial Stock Market Model Revisited*. Springer-Verlag, 2008.

[6] L. Menkhoff, "Examining the use of technical currency analysis," *International Journal of Finance and Economics*, vol. 2, pp. 307–318, 1997.

[7] M. P. Taylor and H. Allen, "The use of technical analysis in the foreign exchange market," *Journal of International Money and Finance*, vol. 11, no. 3, pp. 304–314, June 1992.

[8] C. Hommes, "Heterogeneous agent models in economics and finance," in *Handbook of Computational Economics*, 1st ed., L. Tesfatsion and K. L. Judd, Eds. Elsevier, 2006, vol. 2, ch. 23, pp. 1109–1186.

[9] J. Frankel and K. Froot, *Private Behaviour and Government Policy in Interdependent Economies*. New York: Oxford University Press, 1990, ch. Chartists, fundamentalists and the demand for dollars, pp. 73–126.

[10] B. LeBaron, W. B. Arthur, and R. Palmer, "Time series properties of an artificial stock market," *Journal of Economic Dynamics and Control*, vol. 23, no. 9-10, pp. 1487–1516, September 1999.

[11] B. LeBaron, "Building the santa fe artificial stock market," Brandeis University, Working paper, june 2002.

[12] N. T. Chan, B. LeBaron, A. W. Lo, and T. Poggio, "Agent-based models of financial markets: A comparison with experimental markets," MIT Sloan, Working Paper 4195-01, 2001.

[13] D. K. Gode and S. Sunder, "Double auction dynamics: structural effects of non-binding price controls," *Journal of Economic Dynamics & Control*, vol. 28, no. 9, pp. 1707–1731, 2004.

[14] J. Derveeuw, B. Beaufils, P. Mathieu, and O. Brandouy, "Testing double auction as a component within a generic market model architecture," vol. 599, pp. 47–61, 2007.

[15] S. Crowley and O. Sade, "Does the option to cancel an order in a double auction market matter?" *Economics Letters*, vol. 83, no. 1, pp. 89 – 97, 2004.

[16] S. J. Grossman and J. Stiglitz, "On the impossibility of informationally efficient markets," *American Economic Review*, vol. 70, no. 3, pp. 393–408, 1980.