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An Agent-Based Market Simulation with Social Effects

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ABSTRACT

This paper investigates an agent-based market model with a focus on social effects on agent behavior and market dynamics. To simulate these effects, widely used social network topologies from previous research were incorporated into the model. In this framework, agents select one belief from a set of possible beliefs, including fundamentalism, trend chasing, and interrupting strategies. Belief updating occurs based on two main factors: the historical performance of each agent's own belief and the influence of other agents' beliefs within the network. To formalize this process, a novel opinion formation model was developed, capturing the dynamic interactions among heterogeneous agents. The diversity of agent decisions generates market heterogeneity, reflecting realistic trading behavior. Simulation results demonstrate that returns across all social network topologies replicate key stylized facts observed in real financial markets. Furthermore, the findings highlight the significant impact of social interactions on price formation and market statistics, emphasizing the role of network structure in shaping market behavior. The proposed agent-based framework provides valuable insights into how individual decision-making and social influence jointly contribute to complex market phenomena, offering a robust tool for analyzing the interplay between agent heterogeneity, social effects, and emergent market properties.

1. INTRODUCTION

Nowadays agent-based modeling has found a great place in multidisciplinary studies, such as, Socio-economic, Biophysics and Socio-psychology [1]. Focusing on economic problems, researchers have recently paid more attention to simulation of different types of markets, e.g. stock, FOREX and commodity markets [2,4]. In fact, researchers have investigated the behavioral aspects of investors in a real market. In response to this, rational agents who share the same information about the market are not suitable to make the bubbles and crashes occurred in a real market [5]. This motivates us to use bounded rational agents with heterogeneous beliefs in our market.

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At any case, the main approaches to simulate a market can be fallen into two main categories [3]. One approach is to attribute a set of chromosomes [6] or decision trees [7] to agents. This set can be interpreted as a set of beliefs based on which agents can choose their strategies. Another approach is to attribute a set of time non-variable beliefs to each agent. In this approach agents choose their beliefs based on a defined mechanism. For example, [8] and [9] present an adaptive belief system (ABS) to change the beliefs. [10, 11] present a model consisting of fundamentalists and chartists to represent the bubbles and crashes in a real market. [12,13] employ a method which is able to represents stylized facts based on ants' food finding algorithm. [14] utilized an agent-based market as a artificial laboratory to improve the understanding of Regulatory mechanisms.

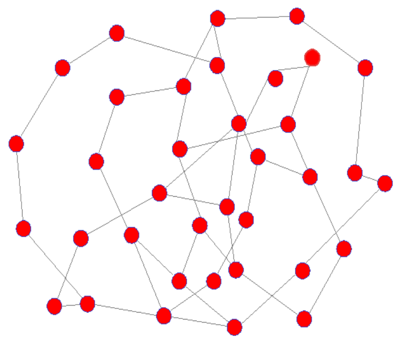
Financial markets are under the influences of social networks. The news about a stock or a brand spread through the social network websites in a matter of seconds. To respond to this issue, researchers have recently introduced social effects into the market models (see [15,17]).

In this paper, a set of initial beliefs has been utilized to construct an agent-based market. Here, the social network models have been introduced into market model presented in [14]. In this paper, three different kinds of agents, i.e. fundamentalists, trend-chasers and interrupting agents have been employed. These agents make the market dynamics possible by their interactions. An opinion formation mechanism has been investigated which simultaneously incorporates the social effects and the wealth of beliefs. Here, the opinion formation model presented in [18] has been modified. In this paper, price movement and other statistics have been investigated also Kurtosis and Skewness have been introduced as criteria to analyze the social effects and the effect of opinion formation model on our market.

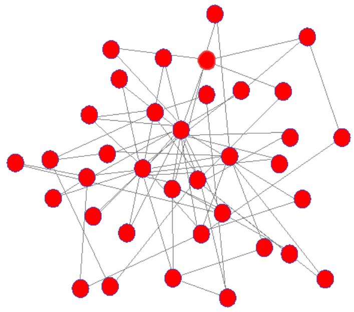
2. MODEL

1.1. Social Networks

Generally, to simulate a social system, the social networks topologies are employed. In this paper, two common used topologies, i.e. Small World (SW) and Scale-Free (SF) have been used. To establish a SW graph the method presented in [19] has been employed. Algorithm starts from a regular circle graph, in which each agent has D neighbors. There is a likelihood π for each agent to make a new connection with a new agent. Fig. 1a shows the SW network with D=2 and$\pi = 0.2$. To construct a SF network, the preferential attachment algorithm presented in [20] has been used. Algorithm starts from a small fully connected network with m0 nodes as a core. Then the next nodes are added to the graph. Each new node should make l links with existing nodes. The more links a node has, the more likely to have a new connection with a new-coming node.



a



b

Fig 1. The social networks 1a) SW 1b) SF

The process of adding new nodes continues to reach a defined number of nodes. Fig. 1b shows the SF network with m0=3 and l = 2.

1.2. Market

Agents following the simple rules choose their strategies affected by conditions. In this paper, three main groups of agents have been employed. These groups are fundamentalists, trend-chasers and interrupting agents. The third group of agents quits the trades.

Our model is based on [14]. In this model, all the agents assign their actions and an agent called market maker gathering the offers clear the market. The mechanism of price clearance used by market maker can be briefed as

$$p_{t+1} = p_t + a\left(\sum_{i\in H} n_t^i D_t^i\right) + \alpha_t \tag{1}$$

In this equation, $p_t = \ln(P_t)$ and P_t is a price at time t. a is positive constant. D_t^i and n_t^i are the demand and the portion of agent of type ith respectively. If excess demand, the part in parenthesis, is positive the price goes up and otherwise goes down. Here a normal random process α_t with mean zero and standard deviation σ^α has been used.

The main idea of trend-chasers is to analyze the price to choose strategies i.e. buying or selling. Generally, they buy (sell) when the price goes up (down). (2) briefs their demand

$$D_t^C = b(p_t\text{-}p_{t\text{-}1}) + \beta_t^C \tag{2}$$

It can be seen from right hand side of (2) that in each time step, current price is compared to previous one. In fact the first part shows a extrapolation for current market trend. b is a positive parameter called reaction parameter. The second part of (2) is normal random process with mean zero and standard deviation σ^C. In contrast, fundamentalists think the price is more likely to converge to its fundamental value. In fact they believe the price goes away from its fundamental value in short-term. Generally, they buy when the price is under the fundamental value and otherwise they sell. Their mechanism of buying and selling could be given by

$$D_t^F = c(f_t\text{-}p_t) + \beta_t^F \tag{3}$$

In this equation f_t is a natural logarithm of fundamental value. c is a positive constant. β_t^F is a normal random process with mean zero and standard deviation σ^F. Based on [14] $f_t = 0$. There is a possibility to choose c and b as random processes in (1) and (2) respectively. This introduces more heterogeneity into the model [21]. But here the model is kept simple.

Now the wealth of each belief must be presented. The agents consider this wealth as their fitness function based on which they choose their beliefs for the next time. The following equations brief these fitness functions

$$W_t^C = (\exp(p_t) - \exp(p_{t\text{-}1}))D_{t\text{-}2}^C + lW_{t\text{-}1}^C \tag{4}$$

$$W_t^F = (\exp(p_t) - \exp(p_{t\text{-}1}))D_{t\text{-}2}^F + lW_{t\text{-}1}^F \tag{5}$$

$$W_t^O = 0 \tag{6}$$

Here W_t^C, W_t^F and W_t^O are the fitness functions for trend-chasers, fundamentalists and inactive agents respectively. Two active groups of agents, consider two factors in their fitness functions. The first part of (4) and (5) shows the previous performance of each belief. The timing in these equations should be noticed. Agents have the memory and $0 \leq \ell \leq 1$ simulate the impact of this memory in their fitness function. Agents with $\ell = 1$ ($\ell = 0$) have perfect memory (no memory).

1.3. Opinion Formation Mechanism

Agents change their beliefs about the market. Two important factors, i.e. the neighbors' beliefs and the wealth of each belief have effect on agents' decisions. Here a mechanism presented in [18] has been modified. Compared to [18], in our opinion formation mechanism all the agents revise their beliefs simultaneously, due to the fast spreading of information in social networks. Our model can be briefed as

$$Pr_k^{h,t} = \frac{exp\ (\gamma \tanh\ (eW^{h,t-1}) + \omega(\#h_k^{t-1}/\#N_k\ ))}{\sum_{i \in H} exp\ (\gamma \tanh\ (eW^{i,t-1}) + \omega(\#i_k^{t-1}/\#N_k\ ))} \quad (7)$$

Here exp is an exponential function. $Pr_k^{h,t}$ is the probability that agent kth is of type h at time t. $W^{h,t-1}$is the wealth of belief of type h and $\#h_k^{t-1}$is the number of agents of type h around the agent kth. $\#N_k$ is the number of all the agents around the agent kth. H is a set of beliefs i.e. H={1,2,3,…,h}. e is a constant. γ and ω are the social network and the wealth of beliefs impacts respectively.

In comparison with main model in which agents get +1 if their belief is profitable otherwise -1, here the wealth of beliefs has been filtered through a hyperbolic tangent. This modification prepares the mechanism to be suitable for the market models with a set of more complex beliefs. In the main model, the number of agents having belief of type h has been considered. In comparison, in the model presented here, the portion of agents with a given belief is important to agents in their decisions. Considering the number of agents with a given belief, can overshadow the filtered wealth of belief, causing market to be stuck in a belief without any change.

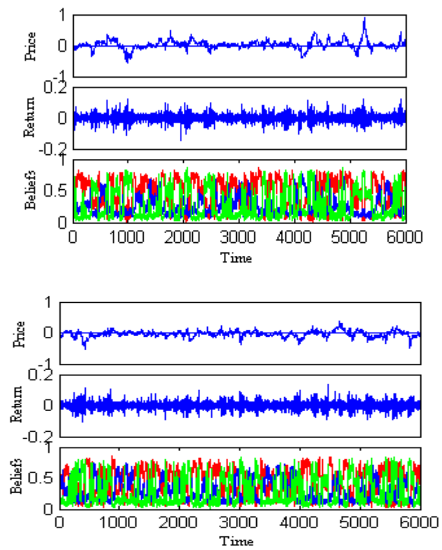


Fig. 2. Price movement, return and evolution of beliefs for a) SF and b) SW. In all the panels, the colors green, red and blue show the portions of trend-chasers, fundamentalists and inactive agents respectively.

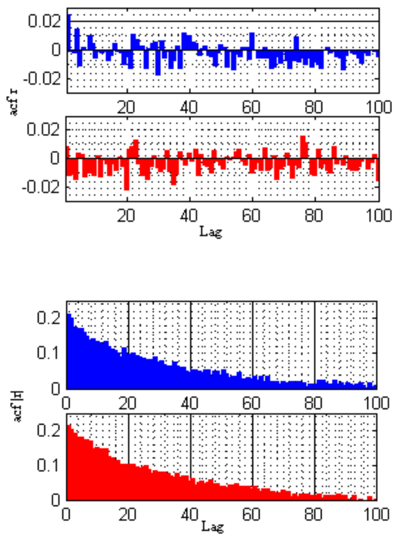


Fig. 3. Autocorrelation of raw return (a) and absolute return (b). In both figures red, stands for SW and blue for SF

3. SIMULATION RESULTS

The parameters values have been chosen based on [14]. The main differences here are e, γ and ω. e should be chosen big enough to magnify the wealth γ and ω have been set at 1. They will be changed whenever needed. Parameters values are assigned as

$a = 1, \sigma^a = 0.01, b = 0.04, \sigma^C = 0.05, c = 0.04$

$\sigma^c = 0.05, c = 0.04, \sigma^F = 0.01, \ell = 0.975$, e=1000

Also the number of agents in social networks is 225.

3.1. Evolution of Beliefs and Price Movement

Figure 2 shows the evolution of beliefs, return and price movement for social networks. Here the simulations have been done for 6000 time periods. As the panels reveal both social networks shows bubbles and crashes. Generally in both figures, when bubbles occur the number of trend-chasers (shown in green) goes up. Also, when price approaches to its fundamental value the number of fundamentalists (shown in red) increases.

Obviously, the increase of trend-chasers makes market more unstable. Kurtosis for both social networks is higher than 3. This means that the model shows the fat tail which is observed in real world markets. Moreover, skewness is around zero for both social networks. To look more closely at kurtosis and skewness, each simulation has been repeated 200 times, and the average on kurtosis has been computed. The result for both social networks is around 5.7 for kurtosis and -.003 for skewness.

Another important statistics to investigate is autocorrelation of return series. In real markets, autocorrelation of return series usually shows zero or close to zero values for the first lags. This means that the prediction of next time periods is not possible. Fig. 3a shows the autocorrelation of raw return for the 100 first lags. As can be seen, this numbers for all the lags and for both social networks are between -0.03 and +0.03. Fig. 3b shows the autocorrelation of absolute return series. This shows the volatility clustering for return series. In real world market, this statistics goes down for the higher lags (such as fig. 3b).

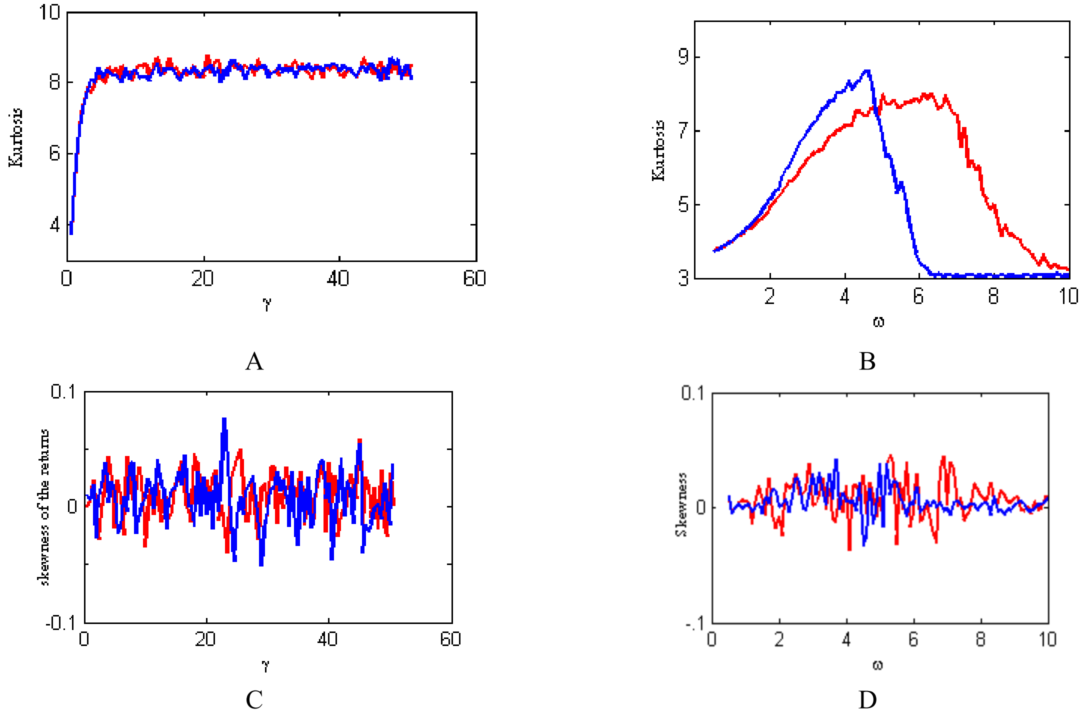


Fig. 4. The results for kurtosis and skewness. In left panels is fixed and changed, while in right ones, is fixed and increases. In all the panels, red stands for SW and blue for SF networks.

3.2. Sensitivity

So far, modes met some stylized facts drawn from the real world market. Here, the sensitivity of the model to the important parameters i.e. and is evaluated. To study the sensitivity is set at 0.5 and changes and vice versa. For each change of any parameter, the simulations have been repeated 200 times with 4000 time steps then the average has been computed over the results. The criteria here are kurtosis and skewness. Fig. 4 shows the results for both social networks. Obviously when changes (fig. 4a) both social networks shows an increasing kurtosis but for higher values of two curves have slightly changes. In fact, when is big enough, the wealth overshadows the social effect in (7), and practically (7) is made into an ABS presented in [8,9]. In contrast, when is increasing the Kurtosis for both social networks goes up and for higher values of it goes down (fig. 4b).

In fact, when increases the social effect in (7) overcomes the wealth impact and after a threshold the social effect is somehow the only factor which is important in agents' decisions. This causes the agents to choose their beliefs more randomly without considering wealth of beliefs. Moreover, the difference between kurtosis curves for the social networks can be attributed to differences between two topologies. Also, fig. 4 shows the skewness for both social networks. As can be seen, for all the figures skewness remained around zero.

4. CONCLUSION

In this paper, a simple agent-based model was developed, modifying an opinion formation mechanism presented in [18]. Based on this modified mechanism the social effects and the wealth of each belief were incorporated. The social networks topologies impacts on market dynamics and statistics were investigated. Also the sensitivity of model was investigated using skewness and kurtosis as the criteria. Results showed the artificial market presented in this paper met the stylized facts.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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