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INFORMATION ASYMMETRY IN THE ARTIFICIAL FINANCIAL MARKET REPRESENTED BY SCALE-FREE NETWORK

Ognjen Radović
Faculty of Economics, University of Niš, Serbia
ognjen.radovic@eknfak.ni.ac.rs

Jelena Stanković
Faculty of Economics, University of Niš, Serbia
jelenas@eknfak.ni.ac.rs

Abstract:
Financial markets are complex systems in which the market price of the financial instruments reflects the distribution of information and investors' expectations. If we regard investors as nodes (vertices) and interacting relations between investors as links (edges), than financial markets can be viewed as complex networks, whose structure corresponds to scale-free networks. Since the classic mathematical models have not yielded satisfactory results in market analysis, in recent years, the complex system analysis is carried out using agent-based models. In this paper we analyze the diffusion of information in the financial market presented by means of a scale-free network. We hypothesize that large investors are better informed than the smaller ones and explain reasons for appearance of information asymmetry between the traders. Considering the assumption that financial market is scale-free network, we present a simple agent-based computational model of the financial market, formed in Netlog and R programming environment, and investigate the effects of distribution of information through network. Simulations of artificial stock market (ASM) model with different number of heterogeneous agents and different priority in orders' realization shows that initial wealth of agents is reallocated in favor of better informed agents. Small and "uninformed" agents can reduce the information gap by imitating the wealthier neighboring agent and increase the wealth. However, favoring realization of large orders can paradoxically improve the position of small agents in the market by reducing the effect of inaccurate anticipation of market movements due to lack of information and efficacy to make precise anticipation.

Keywords: information asymmetry, artificial financial market, scale-free network.

1. INTRODUCTION

In the past years scientists have revealed the presence of complex network structures in various natural and social systems. (Watts & Strogatz, 1998) Transforming elements of the system (agents) into the nodes and interactions in relationships, formally, we can form the network representation of any complex system. (Boccaletti et all, 2006) Financial markets can be also viewed as complex networks, whose structure corresponds to scale-free networks. (Haldane & May, 2011) Scale-free networks show clear structural regularities: a short average path length, a high level of clustering, and the power law node degree distribution. Modern financial markets are complex systems in which the market price of the financial instruments reflects the distribution of information and investors' expectations. Due to the complexity of interpersonal interactions among market participants, which significantly influence their investment decisions, the application of classic mathematical analytic methods has not yielded satisfactory results. Therefore, in recent years the complex system analysis has been carried out using agent-based models. Computational agent-based models emphasize interactions and learning dynamics in groups of traders learning about the relations between prices and market information (LeBaron, 1999).

There are numerous anomalies of the modern financial market, but in this paper authors are dealing with the problem of information asymmetry, which essence lies in the availability of information to participants in the financial market. Besides the impact of information asymmetry, this paper will explore the impact of network structure on the distribution of wealth among the agents. If we take into account the growing importance of social and economic networking, the results of this study show some interesting implications not only on the financial market.

The article is organized as follows. In Section 2, a brief description of the impact of information asymmetry in the financial market is given. In Section 3, we design artificial financial market represented by scale-free networks. A model of artificial stock market (ASM) with heterogeneous agents is proposed and heard behavior of the agents as a method of reducing information gap is analyzed. In Section 4, we analyze the results of computer simulations of the implemented agent-based model of artificial financial market and discuss the impact of information asymmetry, trading mechanisms and network structure to the final distribution of wealth agents. At last, Section 5 concludes.

2. INFORMATION ASYMETRY IN THE FINANCIAL MARKET

Standard neoclassical models of investment are typically based on the assumption that capital markets are efficient and that agents are perfectly rational. Efficient market hypothesis (EMH) emphasizes the role of information in setting prices of the securities in the market and defines the efficient market as one in which prices always "fully reflect" available information. (Fama, 1970) Under such terms, agents do not need to have any direct interactions in order to make investment decisions. It is assumed that agents act rationally and deduce their optimum behavior by logical process from the circumstances of any situation (information on changes of economic variables such as market prices or interest rates), assuming that other agents do likewise. (Palmer et al., 1994) As Axtell (2006) points out, this is false characteristic of a financial market, which is empirically confirmed. In reality, economic agents interact with each other and learn from each other. Economic agents can interact in different ways (Kirman, 1997): some agents trade with each other, other agents imitate or adapt their behavior to other agents, some agents communicate with smaller or larger group of other agents, and finally, agents change their beliefs under the influence of close agents. Moreover, there are economic phenomena or structures that arise from such interactions that can not be anticipated from the characteristics of individual agents. In many situations, aggregated behavior may create some structure and regularities, so the collective behavior may seem "rational" despite the fact that individuals are not (Hildenbrand, 1994).

In recent years, the key assumptions of the perfect capital markets have been challenged, since the modern capital markets are fraught with many problems arising from the market imperfections. Information has become the most important resource of the modern business that influences traders' decisions and forms the price of securities in the capital market. Informational efficient price systems aggregate the set of market-level, industry-level and firm-specific information perfectly into the prices of the securities, so they reflect all available information (Piotroski & Roulstone, 2004). It is assumed that the market-level information is equally available to all market participants, and that all participants face the same degree of systemic risk of the market. However, when it comes to industry-level and specific information, some traders' position is better compared to others, because they are information superior (Piotroski & Roulstone, 2004). This causes the problem of information asymmetry, which essence lies in the availability of information to participants in the capital market. (Haly & Palepu, 2001; Frieden & Hawkins, 2010)

3. ARTIFICIAL FINANCIAL MARKET

In order to simulate the effects of diffusion of information in the stock markets and heard behavior as a strategy for reducing information gap, the authors have build an ASM model based on three main features: mechanism of price formation and orders clearing, heterogeneous artificial trading agents and mechanism of adaptation trading agents' expectation.

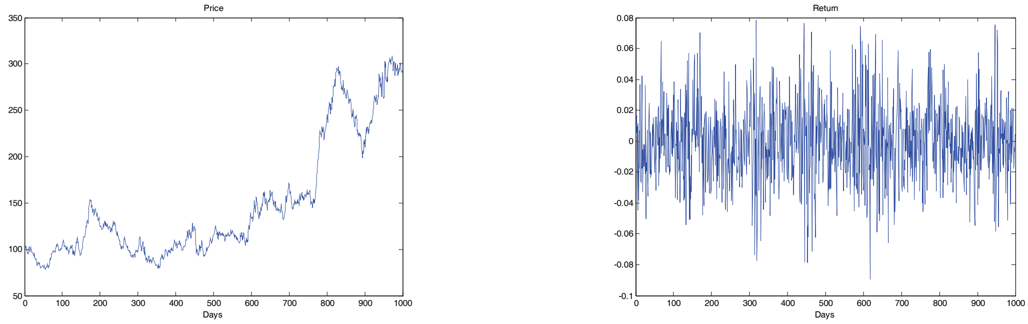
3.1. Mechanism of Price Formation and Orders Clearing

The model used in this simulation is one form of electronic financial markets - crossing network. Crossing networks are basically electronic markets, which directly match sellers and buyers without intermediaries, in trading on the stock basis, using the method of the price formation through the control system of the central order book (Liebenberg, 2002). In the implemented model, in the artificial market heterogeneous agents trade a risky asset - stock. Stock return (r_t) is formed externally, according to normal GARCH (1, 1) model (Bollerslev, 1986):

$$\begin{aligned} r_t &= C + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2) \\ \sigma_t^2 &= \gamma + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \end{aligned} \tag{1}$$

Unconditional variance $\sigma^2 = \gamma / (1 - \alpha - \beta)$ is known to all agents and present the basis for the future stock return predictions (Formula 3).

Figure 1: Generated financial data series of: (a) stock price, (b) stock return in the ASM.



(a) (b)

On the basis of generated stock return, information set (news) is formed and available to trading agents. This news indicates the direction of the stock price change the next day and according to this, the agents try to anticipate the future stock price action and set their order.

3.2. Artificial Trading Agents

According to the defined properties of modeled ASM, agents' portfolio is consisted of one stock (risky asset) and cash (risk free asset). It is assumed that agents optimize the structure of portfolio in the pre-simulation period. Agents can not invest entire cash amount in the risky asset nor just keep the cash, and the size of the order is limited by the agents' wealth.

In the initialization of the model simulation, certain amount of wealth is endowed to all trading agents. The most common situation in ASM models is that all agents have the same amount of initial wealth with an equal share of cash and stocks. However, the objective distribution of wealth would have to reflect the distribution of wealth in real markets. Levy et al. (2000) imply that the number of people with wealth W in a population is proportional to the distribution of wealth by the Pareto law or Boltzmann law of probability distribution. In our model, implemented Pareto distribution of wealth is proportional to the number of neighboring nodes (agents) in the scale-free network. That is, to the nodes with higher degree greater amount of wealth is endowed.

The wealth of the agent i in the period $t+1$ can be presented through the number of stocks $s_{i,t}$:

$$W_{i,t+1} = W_{i,t} R_f + s_{i,t}(p_{t+1} - R_f p_t) \tag{2}$$

where used symbols presents: $W_{i,t}$ – the wealth of the agent i in the period t, $W_{i,0}$ – the initial wealth of agent i, p_t – stock price in the period t, R_f - risk-free return at the risk-free rate $r_f = R_f - 1$, r_t – stock return in the period t, $s_{i,t}$ – the number of stocks in the agent's i portfolio at the period t.

In each period t, agents observe a series of historical stock price movements and form their expectations about the future stock price $E(p_t)$. Their expectations are based on available information set (news) and monitoring the behavior of neighboring agents. This news each agent individually interprets with a certain probability of guessing. It is assumed that wealthier agents anticipate the direction of future stock price movements with higher probability of accuracy. In this model probability of correct anticipation is limited on 0,85 for the wealthiest agent and on 0,5 for the poorest agent.

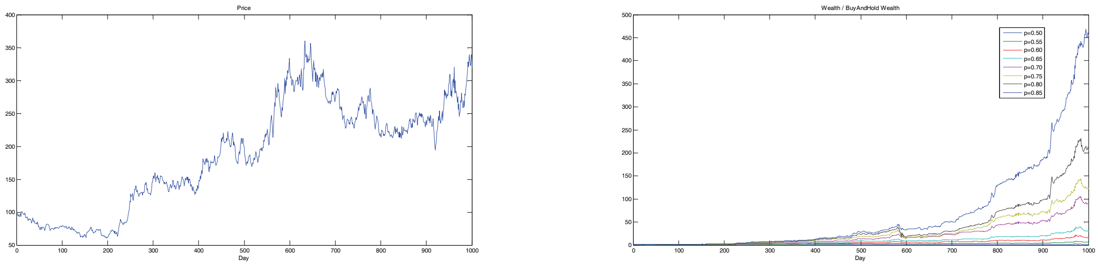
The excepted return of agent i in the period t can be calculated as

$$E(r_{i,t}) = d_{i,t}|\varepsilon_t|, \quad \varepsilon_t \approx N(0,\sigma_t^2) \tag{3}$$

where $d_{i,t} \in \{-1,1\}$ is the direction of stock return movement, which each agent anticipates with certain probability of accuracy $prob_i$ defined at the model initialization proportionally to the agents' wealth.

The effect of individual wealth and anticipation efficiency is shown in Figure 2. The relative change in wealth is measured by the ratio of current wealth of the agent and the potential wealth that he could realize in the case he/she did not trade (Buy and Hold strategy). In Figure 2b it is shown that if the agent has a higher probability of market movement direction anticipation, regardless the inability to accurately anticipate the price in period $t+1$, his/her wealth is gradually increasing, as same as the difference in wealth among trading agents. Therefore, we chose to observe a simulation during 1.000 trading days, because longer period of simulation leads to the domination of a small number of agents and the bankruptcy of most small agents.

Figure 2: The relative motion of the individual agent wealth: (a) one of the ways of stock price path generated during the simulation, (b) relative increase of the wealth of individual agents with different probabilities (p) of future price path anticipation.



(a) (b)

Trading volume of the agent depends on the agent's demand function, which is strongly affected by the agent's utility function. ASM models use different utility functions. Most often, this utility function satisfy CARA or CRRA risk aversion. CARA utility function is used primarily because of the possibility of analytical solution of the utility function. In contrast, despite the more realistic features, CRRA utility is rarely used (Levy et al., 1994, 2000). Our model supports both classes of utility functions.

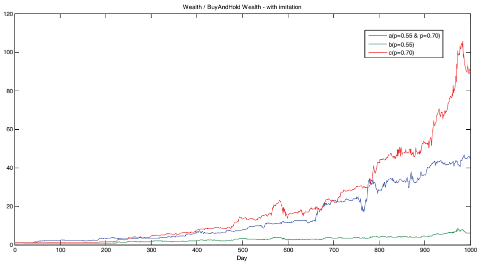
3.3. Heard Behavior among the Neighboring Agents

Agreeable with Hoffman et al. (2007), our model introduces an agents' level of trust defining the relationship between individual expectations and the expectations of wealthier neighboring agent on the future movement of stock price. Accordingly, expectations about market movement of agent i in the period t can be calculated using formula

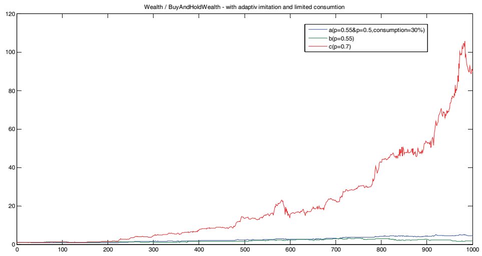
$$E(d_{i,t}) = conf_{i,t} \cdot E(d_{i,t}^{ind}) + (1 - conf_{i,t}) \cdot E(d_{i,t}^{s}) \tag{4}$$

where $conf_{i,t}$ is the level of confidence of agent i at the period t, $E(d_{i,t}^{ind})$ is individual expectation of agent i at the moment t (Formula 3), and $E(d_{i,t}^{s})$ aggregatd expectation of wealthier neighbour agent. In the presented simulation confidence level is fixed and set to 0,5. Agent with the accuracy of probability anticipation p = 0,55 has a richer neighboring agent with the accuracy of probability anticipation p = 0,7. Figure 3 clearly shows that the wealth of the agent during the simulation is significantly increased compared to the situation when there is no imitation.

Figure 3: Relative change of the agent's wealth including effects of imitation and restrictions on trading. (a) Increasing the wealth of an agent, who partly imitates the wealthier agent, (b) Relative increase of the wealth of an agent, who partly imitates the wealthier neighboring agent with restriction on order realization to 30 %.



(a)



(b)

In the presented experiments, the relative change in wealth is based on fully satisfy agents' demand. However, in experiments with a small number of agents and relatively similar trading strategies, agents are often unable to fully realize all trading orders. Figure 3b shows the situation when an agent, who imitates the strategy of wealthier neighboring agent (Figure 3a), is no longer able to carry out all orders. Realization of the order of 30 % almost neutralizes the effects of imitation the successful agent.

3.4. The Model of Adaptation Trading Agents' Expectation

Agent's expectation in the used model is determined by the individual expectation and anticipation of the wealthier neighboring agent. To what extent will the agent "trust" his/her own anticipation of market movements is determined by his/her level of confidence ($conf_{i,t}$). If the wealth of the agent during the observed period increases, it should be expected that the level of his/her self-assurance would be also increased. Otherwise, the agent loses the confidence and trusts the neighboring agents. The initial level of confidence is generated from uniformly distribution U[0,43; 0,77] and set in the following way: the poorest agents start with the minimum confidence level of $conf_{i,t}=0,43$, and the richest agents in the initial model have the maximum level of self-confidence $conf_{i,t}=0,77$. The level of confidence during the simulation period is modified using the Widrow-Hoff learning rules with momentum (Rumelhart et al., 1986):

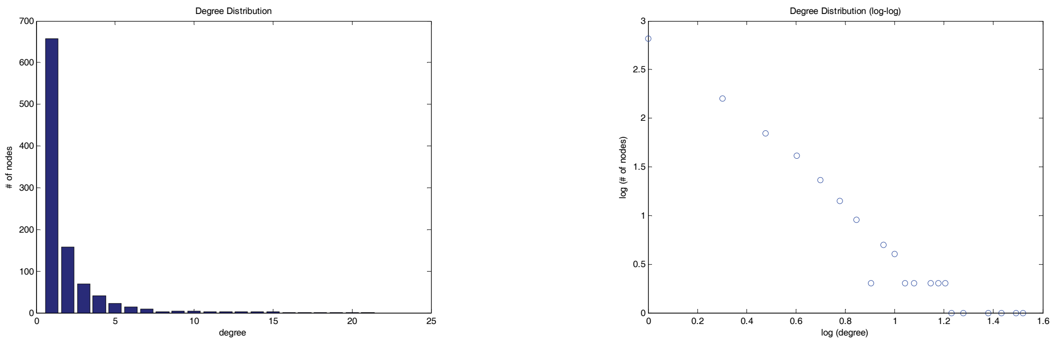
$$conf_{i,t} = \alpha \cdot conf_{i,t-1} - \eta \cdot \frac{\Delta^n W_{i,t}}{\sigma_{i,t}(W_i)} \tag{5}$$

where α is trading agents prejudice set at α = 1, η is the speed of the level of self-confidence change set at η = 0,03, $\Delta^n W_{i,t}$ is a wealth change in selected time period (in used model selected period is the last 100 trading days). After each trading day, all agents modify their level of confidence according to the success achieved in the previous trading day.

3.5. Agents' Formation and Interactions among Agents

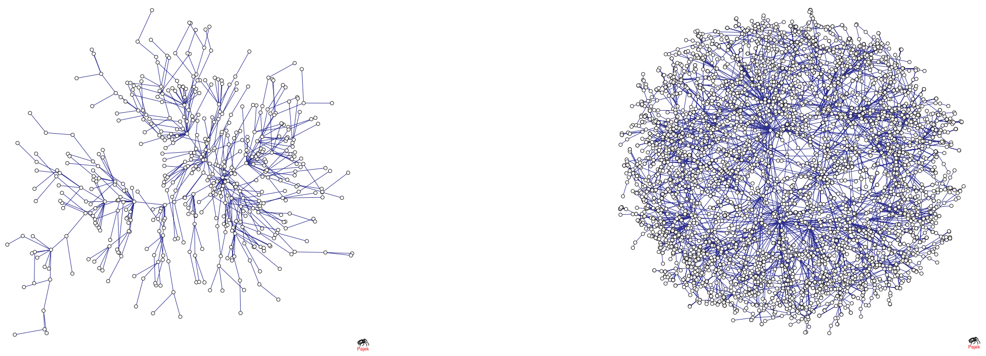
The used ASM model is defined according to the scale-free networks with variable number of nodes, which is characterized by specific distribution of nodes' connection: few nodes have many connections while the most nodes have few connections (Figure 4). The example of two generated networks with 500 nodes and 5.000 is shown in Figure 5. The scale-free network is usually defined by the average short distance between two network nodes. In these networks the average node distance is relatively short.

Figure 4: Degree distribution for sample scale-free network with 1.000 nodes: (a) degree distribution, (b) log-log degree distribution



(a) (b)

Figure 5: The example of scale-free network with: (a) 500 agents, (b) 5.000 agents[1].



(a) (b)

Observed in the context of financial markets, when agents are the nodes, it means that a small number of agents have a very large number of personal contacts, and a large number of agents have a small number of contacts. Agents with a large number of connections are of great importance for the speed of information dissemination through the network. In the used model, the information transmitted to the neighboring agents is the signal of direction of the market movement, which is derived from the type of order sent by the agent. Specifically, if the wealthier agent buys stocks, it is expected that stock price increase in the form of directional movement of the market (+1 for the increase and -1 for the price decrease), which is transmitted to all other agents in the network associated with a concrete agent.

4. RESULTS OF SIMULATION AND DISCUSION

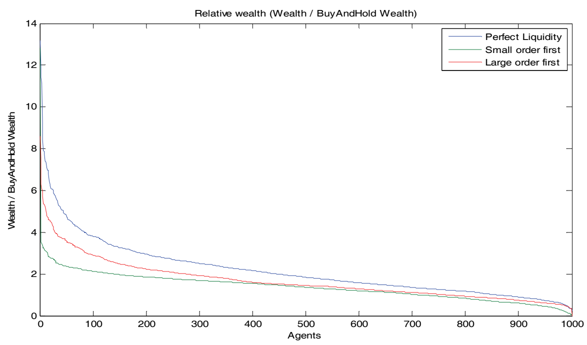
The ASM model simulation starts with generating scale-free networks with predefined and fixed number of agents (Figure 5). Artificial trading agents are ranked according to the number of connections and all relevant parameters of the agents (W_i, $conf_{i,t}$ and $E(d_{i,t})$) are calculated according to such a ranking and set according to Power law distribution. That means that the importance of each agent and his/her strength to influence other agents in the network is approximately inversely proportional to its rank. A certain wealth amount W_0 is

[1] Figures are made in the software Pajek (http://pajek.imfm.si/)

endowed to all trading agents and investment portfolio of each agent is also defined at the beginning of the simulation. In the initial ASM model, the portfolio of each agent is composed of an equal share of risk free asset (cash) and risky asset (stocks). To the poorest agents, i.e. agents with a single connection, following initial portfolio is endowed: number of stocks $s_{i,0}$ = 1.000 stocks, and cash amount $c_{i,0}$ = 100.000 monetary units. The stock price is an exogenous variable and at the beginning of the simulation it is set $p\ (0)$ =100 monetary units. According to the ranking of each agent, efficiency of anticipation the direction of market movement is set for each agent and remains fixed during the simulation. In contrast, the confidence level changes during the simulation, according to the Formula 5. Simulations of 1.000 time steps (trading days) have been performed in the case of both market that priorities execution of large orders and market that priorities execution of small orders. Yields for each simulation step are defined according to Formula 1, with the following parameters C=0.0016, γ=0.0016, α=0.0904, β=0.8658, corresponding to the movement of Microsoft (MSFT) stocks calculated by Zivot (2009). The presented ASM model has been implemented in the programming environment Netlog. The results of simulation and graphical representations are made in the programs Matlab, R and Pajek.

Simulation experiments have been performed with a different structure of scale-free networks and variable number of agent in each experiment. The most important features of the ASM: the number of agents, average distance among reachable pairs and the most distant vertices, are shown in Tables 1 and 2. For each individual network two simulations have been performed during 1.000 trading days. In the first simulation, the priority in trading and order execution has been given to large orders, and in the second trading simulation, trading priority is randomly selected, but, considering the number of small agents, the advantage is given to small orders because they dominate in the total number of trading orders.

Figure 6: The relative change of agents' wealth in a perfectly liquid market, the market that priorities large orders and the market that priorities small orders



Considering defined terms and the structure of the network, it can be concluded that perfectly liquid financial market, similarly to the market that priorities large orders, fulfill the expectations of the wealthiest agents the best. In contrast, market that priorities small orders can not enable that level of wealth increase to the trading agents. Primary reason for that is large number of non-realized large orders, since there is insufficient number of small orders on the counter part.

Table 1: The results of simulation of the ASM with priorities in execution of large and small trading orders

Network (number of nodes)	Average distance among reachable pairs	The most distant vertices	Max Wealth / Buy&Hold Wealth		Average Wealth / Buy&Hold Wealth	
			Large orders	Small orders	Large orders	Small orders
100	4,76141	11	5,092	3,818	1,547	1,325
200	5,76332	16	4,255	5,926	1,450	1,421
300	6,12575	16	6,787	6,276	1,426	1,470
500	6,56791	18	10,567	6,843	1,376	1,520
1.000	7,12490	20	13,195	8,618	2,188	1,638
2.000	7,91867	22	23,363	14,181	2,100	1,624
3.000	8,37180	23	42,433	30,878	2,011	1,725
4.000	8,67817	23	87,299	77,909	1,881	1,598
5.000	8,89457	24	131,941	128,016	1,911	1,913

However, the market that priorities execution of large orders is also suitable for the other agents. Since small agents do not have sufficient efficiency of anticipation, disabling them to realize their orders save them from losses and wealth decrease, which is caused by inaccurate anticipations of market movements.

5. CONCLUSION

In this paper, the authors present the ASM model built according to the scale-free network characteristics. Artificial agents are heterogeneous in the terms of wealth and efficiency in anticipating stock price movement in the market, and with different level of confidence. Heterogeneity of agents derived from the structure of scale-free networks: agents with multiple connections have a higher level of wealth and confidence and better anticipate future market trends. The decision to trade is formed on the basis of individual anticipation, imitation of wealthier neighboring agent, and the level of confidence. At the artificial stock market it is traded with one risky asset, whose price is formed externally to the GARCH stochastic process.

Results presented in this paper show that the imitation of wealthier agents' behavior allows the relative increase of wealth; however, this increase may vary due to the market's microstructure. The mechanism of execution of orders in the market can significantly affect the increase of wealth. The markets that give priority to large orders allow wealthier agents a higher degree increase in the relative wealth in comparison to the market that favors the execution of small orders. Paradoxically, enabling poorer traders to execute orders, market prevents them to achieve greater losses.

The results of this study also indicate that, besides the information asymmetry, the way in which people or economic participants connect with each other influences the distribution of some economic variables. This points to the need for deeper analysis of network structures that people create.

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