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WEALTH DISTRIBUTION IN AN ARTIFICIAL FINANCIAL MARKET WITH AGENT ADAPTATION

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Abstract

The aim of this paper is to analyze the influence of the process of adaptation and network structure on the final wealth distribution of trading agents. The analysis was conducted on an electronic financial market represented by a complex scale-free network. In a trading simulation, the flow of information between the network nodes (traders) influences the decision-making process in terms of investment. The Widrow-Hoff algorithm for adaptation and the size of a complex network are the key aspects of the process. The analysis indicated that the ability to adapt the level of self-confidence and imitate wealthy agents decreases the effect of increase in the network size and maintains the wealth distribution at approximately the same level. Using Pareto's model, we will show a two-fold outcome. On the one hand, the increase in the size of the network and the distance between the nodes increases the even distribution of wealth among the wealthier traders, and increases the gap between the poorer trading agents. The cause of this model behavior can be found in the relatively quick exchange of information between the wealthier trading agents, and the slower exchange between the poorer trading agents. This behavior is a consequence of the increase in the average distance between the network nodes with an increase in the network diameter. The computer model included in the analysis was designed in the NetLogo modeling environment, while the statistical analysis of the complex network was performed using the Pajek and Origin programs.

Key words: scale-free networks, artificial financial markets, wealth distribution

ДИСТРИБУЦИЈА БОГАТСТВА НА ВЕШТАЧКИМ ФИНАНСИЈСКИМ ТРЖИШТИМА СА АДАПТИБИЛНИМ АГЕНТИМА

Апстракт

Основни циљ овог рада је анализа утицаја процеса адаптације и структуре мреже на коначну расподелу богатсва међу агентима трговања. Анализа обухвата електронско финансијско тржиште представљено комплексном мрежом без скале. Током процеса симулације трговине, ток информација између чворова мреже (трговаца) утиче на процес инвестиционог одлучивања. Кључни аспекти овог процеса су Widrow-Hoff-ов алгоритам адаптације и величина комплексне мреже. Анализа је показала да процес адаптације нивоа самопоуздања и имитације богатијих агената смањује утицај пораста величине мреже и одржава дистрибуцију богатства на приближно истом нивоу. Коришћењем Паретовог модела показаћемо две ствари. Са једне стране, повећање величине мреже и растојања између чворова повећава равномерност дистрибуције богатства међу богатијим агентима, и са друге стране, повећава јаз међу сиромашнијим агентима. Узрок оваквог понашања модела лежи у релативно брзој размени информација међу богатијим трговцима и споре размене информација међу сиромашнијим трговцима. Ово понашање последица је повећања растојања између чворова мрежа са повећањем дијаметра мреже. Коришћени рачунарски модел је имплементиран у програмском окружењу NetLogo а статистичка анализа комплексне мреже у програмима Pajek и Origin.

Кључне речи: мреже без скале, вештачка финансијска тржишта, расподела богатства

INTRODUCTION

In financial markets both the information distribution and the investors’ expectations are reflected in the market price of the financial instruments. As complex adaptive systems, these markets can be viewed as a “dynamic network consisting of interacting agents” (Holland, 1995, p. 10). By transferring system elements (trading agents) into nodes and interaction into relations, we can formally obtain a network representation of any complex system (Boccaletti, Latora, Moreno, Chavez & Hwang, 2006).

The modern approach to the analysis of economic systems relies on agent-based modeling, computer models which simulate certain economic occurrences under controlled experimental conditions (Tesfatsion & Kenneth, 2006). While groups of trading agents learn about the relations between prices and market information, computation agent-based models simultaneously emphasize their interactions and the learning dynamics within them (LeBaron, 2000).

The occurrence of scale-free networks was noted in different natural and social systems (Barabási, 2012, pp. 14-16). Different approaches to the use of scale-free networks were developed for the purpose of financial market analyses (Meyers, 2011 and Jiang & Zhou, 2010). The influence of the network structure on the price dynamics of the artificial market was confirmed in the work of Tedeschi et al. (Bargigli & Tedeschi, 2014; Tedeschi, Iori, & Gallegati, 2012; and Tedeschi, Iori & Gallegati, 2009). Social interaction along with the imitation of behavior among agents, which leads to crowd behavior, has been studied by numerous authors (Alfarano, Lux & Wagner, 2005; Kirman, 1993; and Lux & Marchesi, 1999). However, a very small number of papers deal with the different individual factors and preferences of agents, all of which can be found on actual markets, or their influence on the market dynamics represented in the complex network.

This paper illustrates the influence of self-confidence of agents on the dynamics of the increase/decrease of individual wealth. The wealthier (more successful) agents have a higher level of self-confidence and trust their investment decisions. Unsuccessful trading agents lose trust in their own decisions and tend to imitate their more successful neighboring agents (Hoffmann, Jager & Von Eije, 2007). Self-confidence alters during trading and depends on success, i.e. the acquired wealth. These variations can be seen as an adaptive process. Here, agent adaptation is achieved by a change in the level of self-confidence based on Widrow-Hoff learning, depending on the change in wealth. Thus, the wealth of trading agents influences their investment decisions. We could conclude that agents participate in an adaptive investment decision-making process which depends on the acquired wealth, level of confidence, preference function, and imitation of (or advice from) the nearest most successful trading agent.

The computer model was implemented in the NetLogo modeling environment while the statistical analysis of the complex network was carried out in the Pajek and Matlab programs.

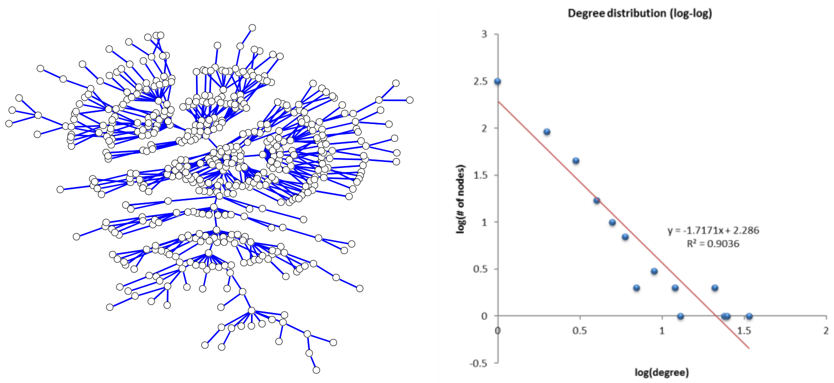
The paper is organized as follows. The second part of the paper offers a more detailed description of the trading mechanisms, the artificial agents and the structure of the implemented complex network. The design of the agent-based artificial electronic financial market is described in the third section. The fourth section presents the results of the simulation.

MODEL FORMATION

An artificial stock market model (ASM), represented by a scale-free network, contains four basic elements: agent organization, artificial trading agents, agent adaptation, and the mechanism of price formation and clearing.

Trading Agent Organization and Network Structure

The agents in our model are organized in the form of a complex scale-free network with a node structure. A small number of agents (or hubs, in the terminology of complex networks) are connected to a large number of other trading agents. However, a larger number of agents have a small number of neighboring agents (Fig. 1).



a) b)

Figure 1. The scale-free network with 500 nodes – graphic representation in Pajek[1] *(a) and degree distribution (b).*
Source: Authors' calculations

The construction of the network model begins with the formation of two nodes and their interconnection. A node is added at each subsequent step. Each new node is then stochastically connected to already created nodes, while the probability proportional to the power of the node, i.e. the likelihood of its clustering with node *i* is:

$$p_i = \frac{k_i}{\sum_j k_j} \tag{1}$$

where k_i is the power of node *i*. All the powers of the already existing nodes are summed up. The nodes which initially established a greater number of connections increase this number based on the principle "the rich become richer" (the Matthew effect). In the context of the financial market, a new agent on the market will most probably monitor the behavior of the best known investor. This is known as "preferential attachment" and the networks built around it, such as the Barabási-Albert one, are known as scale-free networks (Barabási & Albert, 1999 and Albert & Barabási, 2002). The node distribution in such a network has a power distribution $P(k) \sim k^{-3}$. The average length of the path increases logarithmically with the size of the network $l \sim \ln N / \ln\ln N$ while the clustering coefficient increases following the empirically determined distribution power law $C \sim N^{-0.75}$.

[1] http://pajek.imfm.si/

In the studied artificial market, the portfolio of each trading agent consisted of a certain amount of shares (stocks) and cash (a risk-free asset). Only high-risk assets were traded. The decisions made regarding investments were based on the optimization of the composition of the portfolio during one simulated period, one day ahead. At the beginning of the simulation, all the trading agents were allocated a certain amount of wealth. In actual markets, wealth distribution is not proportional. Levy and Levy (2000) cite that the distribution of wealth is in accordance to the Pareto law or Boltzmann's probability equation. However, most ASM models, trading agents, are allocated equal amounts of cash and shares with equal wealth distribution. The choice of uniform wealth distribution enabled us to study the effect of the structure of a complex network on wealth distribution at the end of the simulation.

The wealth of the trading agent *i* in the time span *t,* is given as:

$$\omega_{i,t} = c_{i,t} + s_{i,t} p_t \tag{2}$$

where $w_{i,t}$ is the wealth of the agent *i* at a particular point *t*, p_t is the price per share at point *t*, $s_{i,t}$ is the number of shares contained within the portfolio of agent *i* at point *t*, and $c_{i,t}$ is the amount of cash at point *t.*

At the beginning of every simulation period, all of the trading agents decided on the amount they were ready to invest in the shares in their portfolio, and how much they wished to keep in the form of cash. The expected yield of agent *i* at a point in time *t* was calculated using the following equation:

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

where $d_{i,t} \in \{-1,1\}$ is the path of the agent's future stock price predictions with a probability of $prob_i$ proportionally to the number of neighboring nodes, and it is assigned to all the agents at the beginning of the simulation. Agents with a greater number of nodes have a greater probability of correctly predicting future price movement. We might say that the prediction distribution is in accordance with the distribution of the nodes (Radović & Stanković, 2012).

Agents could not invest their entire assets into shares, keep only their cash, or do short-term selling. Some studies have shown that investors usually keep from 30% to 55% of their wealth in stocks. Without this limitation, a great number of agents could quickly go bankrupt and disrupt the model dynamics.

The size of the trading order indicates that the market depends on its utility function. In this paper we relied on the utility function which satisfies the Constant Relative Risk Aversion (CRRA) (Petrović, Radović

& Stanković, 2011). The utility function determines the portion of the wealth the agent is willing to invest further. Generally, in each round of trading, based on the predictions of future movement, agents evaluate how much their current portfolio composition deviates from the target. If they determine that they have more risky instruments, they attempt to sell the excess share of instruments with a trading order in the determined excess sum. However, if a shortage in the risky instruments was noted, the agents exercised a trading order in the amount of the determined deficiency. The choice of the utility function of the agent, the prediction of the price, and volatility also influenced the demand.

Imitating The Investment Decisions of Neighboring Agents

The evaluation of the influence of the complex network structure on agent prediction, and thus the distribution of wealth, was introduced into the model through the implementation of the imitation of the decisions of neighboring agents.

Inspired by the work of Hoffmann et al. (2007), in our model we introduced a level of confidence for the agents, which was used to determine the relation between individual anticipations and the anticipation of the neighboring agent on the future movement of the share price. The only neighboring agent who is "imitated" is the agent with the greatest number of nodes. The anticipation in the direction of market movement of agent *i* at a point in time *t* is given in:

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

where $conf_{i,t}$ is the confidence level of agent *I* at point *i*, $E(d_{i,t}^{ind})$ is the individual anticipation of the agent *i* at a point in time *t* (based on (3)), while $E(d_{i,t}^{s})$ is the anticipation of the neighboring agent which is visible to the agents as the type of order being executed (buying or selling). As opposed to Hoffmann et al. (2007), in our model the level of self-confidence differs between the agents and fluctuates during the simulation. In addition, instead of a uniform distribution, as in the case of Hoffmann et al. (ibid.), the original level of self-confidence is individually set based on the power interval *U* [0.43, 0.77].

Agent Adaptation – the Widrow-Hoff Learning

Widrow-Hoff learning or delta learning is a gradient adaptive procedure during which we adjust the model with each deviation from the desired target. The level of confidence during the simulation period is modified using the Widrow-Hoff learning rules with momentum (Rumelhart, Hinton & Williams, 1986 and Widrow & Hoff, 1960)

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

where α is the trading agent's prejudice set at α = 1, η is the speed of change of the level of self-confidence set at η = 1.0, and $\Delta^n W_{i,t}$ is the wealth change in the selected period (in the used model the selected period is the last 15 trading days).

If the agent's wealth increases during the studied period (in this model it is a period of 15 days), we should expect that its level of self-confidence will also increase. Otherwise, the agent loses his self-confidence and increases his reliance on the neighboring agents.

The Mechanism for Price Formation and Clearing

The implemented model of the artificial financial market is based on a special electronic financial market, i.e. a so-called crossing network. Crossing networks for trading accounts are markets which directly link the agents without intermediaries for trading on the stock exchange, forming prices using the system of management of the central order book (Liebenberg, 2002). The price at which the transaction takes place is not formed using a special mechanism for price formation, and is instead taken from the primary market. This enables cheaper trading and provides independence from continued liquid asset trading.

The created model is based on the efficient market hypothesis (EMH) that individual trading agents are too "small" to influence the market trends and the manner in which the price is formed. The use of an internal mechanism for price formation in an artificial market with a relatively small number of agents disrupts the EMH. As a result, in this study we focused on a market model based on the mechanism of price formation used in crossing networks. The price of the transaction is introduced externally as a stochastic process.

In the implemented model, the artificial market possesses a type of high-risk financial instrument – stocks. Stock return (r_t) is formed externally as the normal GARCH (1,1) (Bollerslev, 1986):

$$r_t = C + \varepsilon_t,\ \varepsilon_t \approx N(0,\sigma_t^2) \text{ and } \sigma_t^2 = \gamma + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

The unconditional variance $\sigma^2 = \gamma / (1 - \alpha - \beta)$ is known to all the agents and represents the basis for the formation of their anticipation in (3).

The trading between agents is simulated by a random sample of agents with selling orders and agents with buying orders. The size of the transaction is formed based on the size of the smaller order, while the agent with the remaining order remains within the trading process.

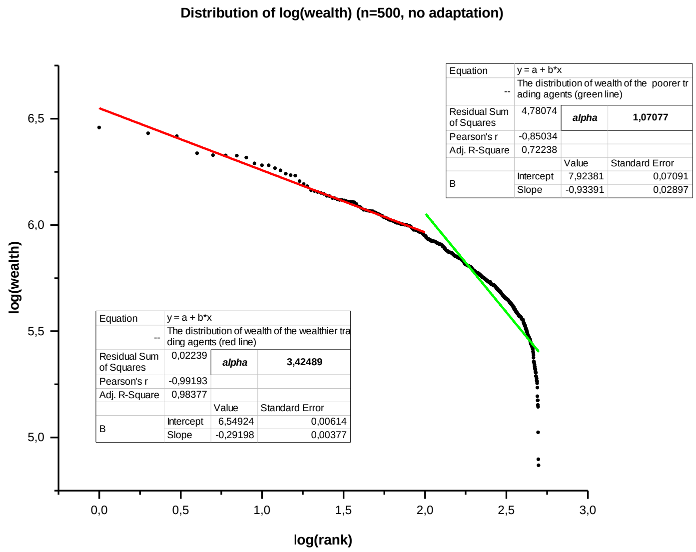
THE RESULTS OF THE MODEL SIMULATION AND THE DISCUSSION

The first step in the simulation process is the generation of a complex network based on the Barabási-Albert algorithm (Barabási & Albert, 1999 and Albert & Barabási, 2002). The number of agents, i.e. nodes in a network, is the only parameter which is set in this step. The process of designing a network represents an initialization of the trading simulation procedure in an artificial market. Based on the network structure, or more precisely, the power of each node, the agent is assigned a particular rank in the network. The agent (node) of the highest power is assigned the rank of 1. According to the power law (the number of connections), the agents are assigned probability of the future price path anticipation $prob_i$ in (3). The probability of predicting the highest ranking agents is a parameter model, and in our simulation it is set at a value of $prob_1=0.85$. The probability of the remaining agents decreases based on their previous rank, and for agents of the lowest rank it is slightly higher than 0.5. The prediction probability remains constant during the entire simulation process. Similarly, the confidence level *conf* in (4) initially has the highest value for the agent of the highest rank. The agent of the highest rank has a level of self-confidence of $conf_1=0.77$ while the agents of the lowest rank have a confidence level of $conf_i=0.43$. The confidence level changes dynamically during the simulation based on the trading success.

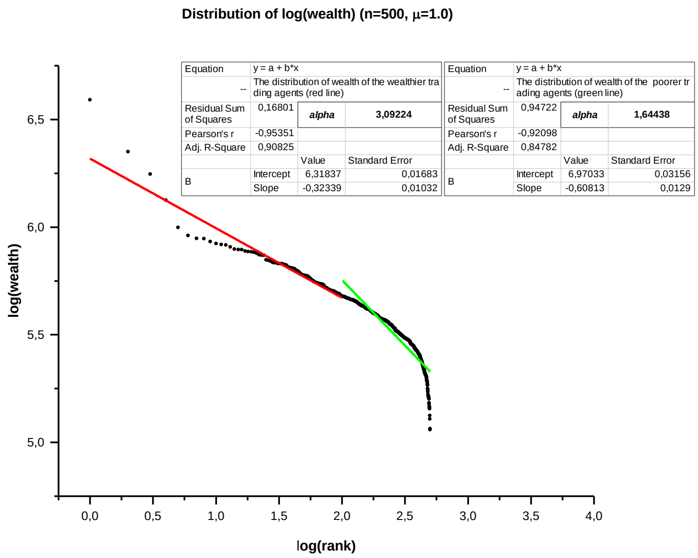
All of the agents were allocated the same amount of wealth W_0 with an equal share in cash and stocks. To be more precise, at the beginning of the simulation, all of the agents were assigned the same amount of cash, $c_{i,0} = 100\ 000$ in monetary units and $s_{i,0} = 1000$ in stocks.

The artificial market represents an electronic crossing network. Considering the fact that the stock price being traded is formed on an external market, it is an exogenic variable in the model. At the beginning of the simulation, the stock price was set at a value of $p(0)=100$ monetary units. During each step of the simulation, the market contributed to the calculations based on (6), with the following parameters: $C=0.0016$, $\gamma=0.0016$, $\alpha=0.0904$, and $\beta=0.8658$. The parameters were taken from the work of Zivot (2009) and describe the dynamics of the change in the stock of the Microsoft (MSFT) company. The trading simulation was carried out in 1000 simulation steps (days of trading). The model supports various mechanisms for allocating order priority. In this paper, we opted for a trading mechanism which provides perfect liquidity. That is, all of the orders could be executed.

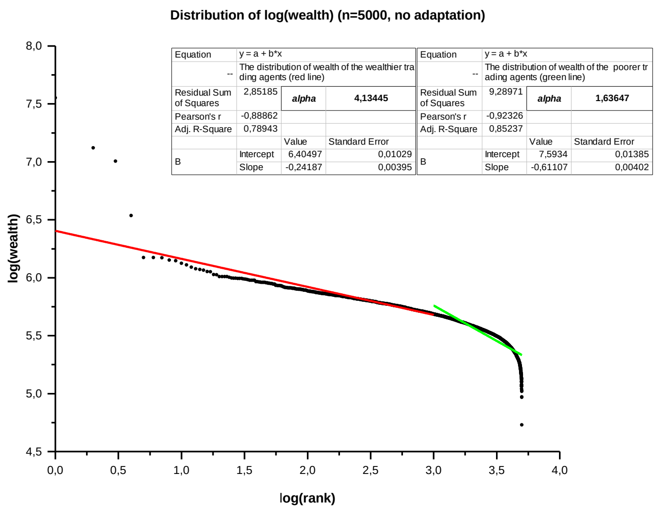
In order to analyze the wealth distribution, we relied on the Pareto model, which means that in this study a small part of the population possesses a larger portion of the wealth.


Distribution of log(wealth) (n=500, no adaptation)
Equation
y = a + b*x
--
The distribution of wealth of the poorer trading agents (green line)
Residual Sum of Squares
4,78074
alpha
1,07077
Pearson's r
-0,85034
Adj. R-Square
0,72238
Value
Standard Error
B
Intercept
7,92381
0,07091
Slope
-0,93391
0,02897
Equation
y = a + b*x
--
The distribution of wealth of the wealthier trading agents (red line)
Residual Sum of Squares
0,02239
alpha
3,42489
Pearson's r
-0,99193
Adj. R-Square
0,98377
Value
Standard Error
B
Intercept
6,54924
0,00614
Slope
-0,29198
0,00377
log(wealth)
6,5
6,0
5,5
5,0
0,0
0,5
1,0
1,5
2,0
2,5
3,0
log(rank)

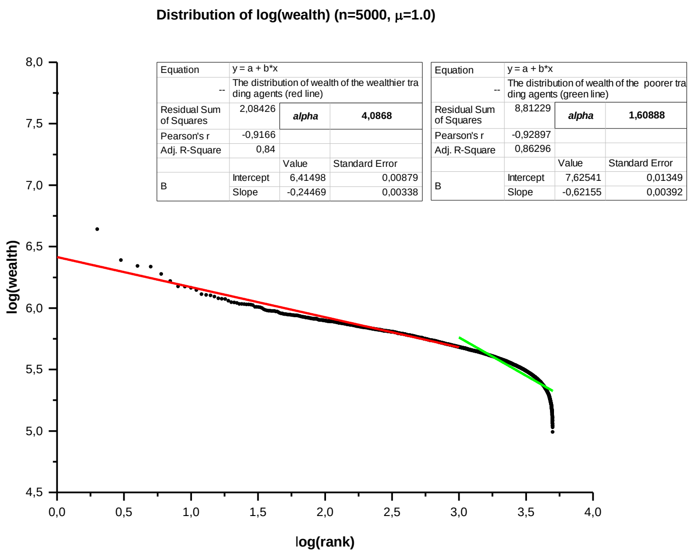
(a)


Distribution of log(wealth) (n=500, μ=1.0)
Equation
y = a + b*x
--
The distribution of wealth of the wealthier trading agents (red line)
Residual Sum of Squares
0,16801
alpha
3,09224
Pearson's r
-0,95351
Adj. R-Square
0,90825
Value
Standard Error
B
Intercept
6,31837
0,01683
Slope
-0,32339
0,01032
Equation
y = a + b*x
--
The distribution of wealth of the poorer trading agents (green line)
Residual Sum of Squares
0,94722
alpha
1,64438
Pearson's r
-0,92098
Adj. R-Square
0,84782
Value
Standard Error
B
Intercept
6,97033
0,03156
Slope
-0,60813
0,0129
log(wealth)
6,5
6,0
5,5
5,0
0,0
0,5
1,0
1,5
2,0
2,5
3,0
3,5
4,0
log(rank)

(b)



(c)



(d)

Figure 2. The distribution of wealth of the wealthier trading agents (red line) and the poorer trading agents (green line) for the various network dimensions and adaptations:
a) a network with 500 agents, without adaptation;
b) a network with 500 agents, with adaptation;
c) a network with 5000 agents, without adaptation; and
d) a network with 5000 agents, with adaptation
Source: Authors' calculations

Levy and Solomon (1997) state that the number of people with a wealth of W in a certain population is proportional to that wealth following the Pareto law:

$$P(W) \approx W^{-1-\alpha} \tag{7}$$

where α is the Pareto exponent. By accepting the hypothesis that the Pareto model of wealth distribution is not ideal (Gonzalez-Estevez, Cosenza, Lopez-Ruiz, & Sanchez, 2008 and Radović & Tomić, 2010), in our study we divided the chosen population into two parts: a wealthier and poorer population. For each of the groups, the Pareto exponent was studied individually.

The calculated values of the Pareto exponents and the graphic representation of wealth are shown in Fig. 2. The higher value of the exponent indicates a more even distribution of wealth.

The studied population of agents was organized according to the relative change in wealth, from the biggest to the smallest, and thus each agent was assigned a position on that list. The Pareto model can then be described in the following manner (Levy & Solomon, 1997):

$$\omega_i = A r_i^{-\frac{1}{\alpha}} \tag{8}$$

where ω is the relative wealth of the agent, r is the position which the agent takes on the organized list according to the values of its relative wealth, A is the constant, and α is the Pareto exponent. By showing the relative values of the change in wealth on the log-log scale, we approach an approximate linear dependence.

The agents were divided into two groups: the first group, with 20% of the wealthier half of the agents and the second group with 80% of the poorer group of agents. For both groups, we calculated the parameters of the linear regression model with the logarithm of wealth in (8). The higher value of the Pareto exponent indicates a more equal distribution and a sharper decline in the distribution curve. The analysis of the Pareto exponent of the wealthier agents (red line) indicates that the Pareto exponent increases with the size of the network.

The influence of agent adaptation in networks with a small number of nodes (n=500) decreases the equal distribution of wealth among the wealthier group of agents (α=3.424 vs. α=3.092) and increases it among the poorer group of agents (α=1.101 vs. α=1.644). However, the influence of adaptation in the case of networks with a large number of nodes (n=5000) is not that pronounced (α=4.134 vs. α=4.087 among the wealthy, and α=1.636 vs. α=1.609 among the poor agents). Previous research (Radović & Stanković, 2012) indicates that the equal distribution of wealth among the wealthier agents increases with the increase in the size of the network *s*, and decreases among the poorer agents (a balancing effect). In larger networks, the average distance between the poorest and the wealthiest agents increases, so that during trading only the nearest agents increase their power of prediction and thus their wealth. The poorer agents are too distant and their trading is at the level of accidental hits, which leads to their unequal wealth distribution. In the adaptation process, the poorer agents lose confidence over time, and increasingly imitate the more successful ones, neutralizing the influence of distance in the network. In smaller networks, the poor agents quickly imitate the most successful ones, which leads to an increase in the equal distribution of wealth among the poorer agents. However, the wealthiest agents modify their level of confidence less frequently, and their increase in wealth is related only to their power of prediction.

CONCLUSION

Our artificial financial market model had the structure of a complex scale-free network with nodes representing the trading agents. The ability to predict the future movements of prices is proportional to the number of connections. The trading agents with the greatest number of connections have the highest level of prediction of the direction of market movement. The trading agents with the smallest number of connections predict at the level of accidental predictions. All of the agents trade on the basis of individual predictions and the predictions of the wealthiest nearest neighbor. Confidence in one's own ability to predict is manifested in the level of self-confidence, which increases with the increase in an agent's wealth and decreases with the decrease in their wealth.

In this paper we have shown that the size of the network can influence the final distribution of wealth between agents who initially had the same amount of wealth. With the increase in the network dimension, we see an increase in the equal distribution of wealth among the wealthiest agents, and a decrease among the poorest agents. Agent adaptation has a balancing effect in networks of greater dimensions, so that the wealth distribution among the poorer agents is maintained, while it does not change significantly among the wealthier ones. However, in the case of networks of smaller dimensions, the equal distribution of wealth increases among the poorest agents and decreases among the wealthier agents.

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ДИСТРИБУЦИЈА БОГАТСТВА НА ВЕШТАЧКИМ ФИНАНСИЈСКИМ ТРЖИШТИМА СА АДАПТИБИЛНИМ АГЕНТИМА

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Резиме

Велики број природних и друштвених система могу се описате као системи састављени од великог броја међусобно повезаних компоненти. Структура ових компоненти и веза као и динамике система може се описати комплексним мрежама. Чворови мреже одговарају компонентама система а везе између њих релацијама међу компонентама. Комплексне мреже могу имати различите структуре. Комплексне мреже које одговарају структури попут Interneta или Weba називамо Scale-free мрежама. Ове мреже имају мали број чворова са изразито великим бројем веза и велики број чворова са малим бројем веза. Природан начин моделирања и симулације система са структуром комплексне мреже је приступ заснован на агент-базираном моделирању. Агент-базирано моделириање (АБМ) омогућује изградњу и симулацију сложених модела са великим бројем хетерогених агената, посебно у ситуацијама када се на основу особина појединачних агенате не може предвидети понашање целокупног система. АБМ приступ омогућује агентима да интерагују међусобно и/или са околином. Овакав приступ је заинтригирао велики број истраживача који се баве економским и финансијским моделирањем.

У овом раду проучавамо утицај структуре сцале-фрее мреже на богатство трговаца на електронском финансијском тржишту представљеном комплексном мрежом. Основни елементи имплементираног модела су организација агената (трговаца), опис агената, адаптација агената и механизам формирања цене. Вештачки агенти организовани су у структуру scale-free мреже и представљни су чворовима мреже. Сви агенти располажу одређеном количином богатства коју чине

готовина (cash) и акција (shares). Током симулације, величина богатства се мења према успеху у трговању. Моћ предвиђања агената пропорционална је њиховој позицији у мрежи. Успех у предвиђању будуће цене утиче на ниво самопуздања агената и ниво имитације суседних агената. Процес адаптације агената имплементиран је помоћу Widrow-Hoff механизма учења.

Резултати симулације показују да се са повећањем величине мреже, дијаметра и растојања између чворова утиче на коначну расподелу богатства међу агентима који су иницијално имали исто богатство. Са порастом димензије мреже повећава се равномерност дистрибуције богатства у групи богатијих трговаца а повећава јаз међу сиромашнијим трговцима. Узрок оваквог понашања модела лежи у релативно брзој размени информација међу богатијим трговцима и спорој размени информација међу симомашнијим трговцима као последица повећања просечног растојања чворова мреже са повећањем дијаметра мреже. Адаптација агената има уравнотежујући ефекат код мрежа већих димензија тако да се расподела богатсва међу сиромашнијим агентима одржава а међу богатијим не мења значајно. Насупрот томе, код мрежа малих димензија расте равномерност расподеле богатства међу сиромашнијим агентима а опада међу богатијим агентима. Рачунарски модел је имплементиран у програмском окружењу NetLogo а статистичка анализа комплексне мреже у програмима Pajek и Matlab.