Risk Impact in the Simulation: What Effects Brings Tobin Tax Involvement on the Stability of Financial Market?

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Abstract
The aim of this paper is to study the influence of Tobin tax on the stability of financial market in the simulation. Particularly, risk analysis is introduced. The method, which is the core of this contribution, is agent-based modeling and simulation. This method is often used to study complex social systems. Agent-based model consists of a set of agents and a framework for simulating their decisions and interactions. In practice, each agent has only partial knowledge of other agents and each agent makes its own decisions based on the partial knowledge about other agents in the system. We used this approach to simulate the behavior of financial market participants trading with assets. For purposes of this paper, a multi-agent system will be implemented as a simulation framework in JADE development platform. The hypothesis of this research is that Tobin tax introduction will stabilize the financial market. The results obtained show its influence on the financial market firstly without and secondly with risk element involved.

Keywords: agent-based, financial market, stability, Tobin tax, risk analysis
JEL codes: C53, C63, C90, E37, E44

1. Introduction

Computational social science involves the use of agent-based modeling and simulation (ABMS) to study complex social systems (Kaegi, 2009; Epstein and Axtell, 1996). ABMS consists of a set of agents and a framework for simulating their decisions and interactions. ABMS is related to a variety of other simulation techniques, including discrete event simulation and distributed artificial intelligence or multi-agent systems (Law and Kelton, 2000; Pritsker, 1995) Although many traits are shared, ABMS is differentiated from these approaches by its focus on finding the set of basic decision rules and behavioral interactions that can produce the complex results experienced in the real world (Sallach and Macal, 2001). ABMS tools are designed to simulate the interactions of large numbers of individuals so as to study the macro-scale consequences of these interactions (Tesfatsion, 2001; Szarowská, 2010). Each entity in the system under investigation is represented by an agent in the model. An agent is thus a software representation of a decision-making unit. Agents are self-directed objects with specific traits and typically exhibit bounded rationality, that is, they make decisions by using limited internal decision rules that depend only on imperfect local information. In practice, each agent has only partial knowledge of other agents and each agent makes its own decisions based on the partial knowledge about other agents in the system. (Conzelmann et al, 2004; Lote, 2007)

Intelligent agent technology used in this paper has deeper roots in economic theory history, mainly in the ideas of F.A. Hayek and H.A. Simon. One of the main ideas of F.A. Hayek is that the economic system should be studied from bottom. He stresses the need to look at the market economy as to a decentralized system consisting of mutually influencing individuals (the same goes for financial markets) in his work. In "Individualism and Economic Order" Hayek (1949) writes: "There is no other way to understand social phenomena such as through our understanding of the actions of individuals who are oriented towards other people and management according to their expected behaviors." He opposed mainly against collectivist theories which claim to be able to fully understand the social right, regardless of the individuals who constitute them. This approach builds a contrast with the assumption of perfect information, which is used in traditional equilibrium analysis. In the theory of complex systems, where Agent-based Modelling and Simulation (ABMS) clearly belongs, is this idea the primary principle (Macal and North, 2006; Stefanescu and Stefanescu, 2013). Agents, unlike classical equilibrium approach have not perfect information about all processes in the system.

The transaction costs on the financial market are mainly the costs of the obtaining and the interpreting of the information, the time required for decision making, various types of fees, etc. Transaction costs according to Burian (2010) are often viewed as negative phenomena, but there are cases where the increase in the transaction costs can be viewed positively and can contribute to the stability of the market. The increase in the transaction costs may also occur in the form of non-market regulation such as the taxes. In the early seventies the Nobel laureate in the economics James Tobin drafted the regulation of currency markets. Tobin suggested that all short-term transactions should be taxed at a low fixed rate (the proposal was later identified as the so-called Tobin tax). The results according to Tobin would avoid short-term currency speculation and stabilize the market. Currency speculation can lead to the sudden withdrawal of the currency from the circulation in order to artificially increase the price. The consequence for the economy of the countries that use this currency may be a temporary reduction in liquidity, problems in obtaining loans and other phenomena (Gallová and Řepková, 2011; Gongol, 2012; Stoklasová, 2012) that can lead to the reduced growth or even to the recession. Tobin tax was never implemented.

For our research work, a multi-agent system will be implemented which is able to deal with unpredictable phenomena surrounding every company nowadays. Multi-agent system will be developed and managed as a simulation framework in JADE development platform (JAVA programming language). The motivation of this research is to investigate the reaction of financial market on the higher transaction costs and risk application. A multi-agent financial market model and simulation is further introduced. Intelligent agents follow technical and fundamental trading rules to determine their speculative investment positions. We consider direct interactions between speculators due to which they may decide to change their trading behavior (Spišák and Šperka, 2011; Šperka and Spišák, 2012). For instance, if a technical trader meets a fundamental trader and they realize that fundamental trading has been more profitable than technical trading in the recent past, the probability that the technical trader switches to fundamental trading rules is relatively high. In particular the influence of transaction costs and risk is studied. This paper is structured as follows. Section 2 firstly describes the original mathematical model, secondly informs about previous simulation results, and lastly represents the hypothesis. Section 3 presents the original simulation results of the agent-based model of financial market.

2. Model Description

2.1 Original Model

The model developed by Frank Westerhoff (2009) was chosen for the implementation. It is an Agent-based model, which simulates the financial market. Two base types of traders are represented by agents:

- **Fundamental traders** - their reactions are based on fundamental analysis – they believe that asset prices in long term approximate their fundamental price – they buy assets when the price is under fundamental value.
- **Technical traders** - decide using technical analysis – prices tend to move in trends – by their extrapolating there comes the positive feedback, which can cause the in-stability.

Price changes are reflecting current demand excess. This excess is expressing the orders amount submitted by technical and fundamental traders each turn and the rate between their orders evolves in a time. Agents regularly meet and discuss their trading performance. One agent can be persuaded to change his trading method, if his rules relative success is less than the others one. Communication is direct talk one agent with other. Communicating agents meet randomly – there is no special relation-ship between them. The success of rules is represented by current and past profitability. Model assumes traders ability to define the fundamental value of assets and the agents behave rationally.

The price is reflecting the relation between assets that have been bought and sold in a turn and the price change caused by these orders. This can be formalized as a simple log-linear price impact function.

$$P_{t+1} = P_t + a\left(W_t^C D_t^C + W_t^F D_t^F\right) + a_t \qquad (1)$$

Where a is positive price adjustment coefficient, D^C are orders generated by technical agents while D^F are orders of fundamental ones. W^C and W^F are weights of the agents using technical respectively fundamental rules. They are reflecting current ratio between the technical and fundamental agents. α brings the random term to the Equation 1. It is an IID normal random variable with mean zero and constant standard deviation σ^α.

As was already said, technical analysis extrapolates price trends – when they go up (price is growing) agents buy the assets. So the formalization for technical order rules can be like this:

$$D_t^C = b\left(P_t - P_{t-1}\right) + \beta_t \qquad (2)$$

The parameter b is positive and presents agent sensitivity to price changes. The difference in brackets reflects the trend and β is the random term – IID normal random variable with mean zero and constant standard deviation σ^β.

Fundamental analysis permits the difference between price and fundamental value for short time only. In long run there is an approximation of them. So if the price is below the fundamental value – the assets are bought and vice versa – orders according fundamentalists are formalized:

$$D_t^F = c\left(F_t - P_t\right) + \gamma_t \qquad (3)$$

The parameter c is positive and presents agent sensitivity to reaction. F represents fundamental value – we keep as constant value to keep the implementation as simple as possible. γ is the random term – IID normal random variable with mean zero and constant standard deviation σ^γ.

If we say that N is the total number of agents and K is the number of technical traders, then we define the weight of technical traders:

$$W_t^C = K_t / N \qquad (4)$$

And the weight of fundamental traders:

$$W_t^F = \left(N - K_t\right)/ N \qquad (5)$$

Two traders meet at each step and they discuss about the success of their rules. If the second agent rules are more successful, the first one changes its behavior with a probability K. Probability of transition is defined as (1-δ). Also there is a small probability ε that agent changes his mind independently. Transition probability is formalized as:

$$\begin{aligned}
&K_t = \left(K_{t-1} + 1\right) \textit{ with probability } p_{t-1}^{+} = \frac{N - K_{t-1}}{N}\left(\varepsilon + \left(1-\sigma\right)_{t-1}^{F\to C}\frac{K_{t-1}}{N-1}\right),\\
&K_t = \left(K_{t-1} - 1\right) \textit{ with probability } p_{t-1}^{-} = \frac{K_{t-1}}{N}\left(\varepsilon + \left(1-\sigma\right)_{t-1}^{C\to F}\frac{N-K_{t-1}}{N-1}\right),\\
&K_t = K_{t-1} \textit{ with probability } 1 - p_{t-1}^{+} - p_{t-1}^{-}. \qquad (6)
\end{aligned}$$

Where the probability that fundamental agent becomes technical one is:

$$\left(1 - \delta_{t-1}^{F\to C}\right) = 0{,}5 + \lambda \textit{ for } A_t^C \rangle A_t^F ,$$

$$\left(1-\delta_{t-1}^{F\to C}\right)=0{,}5-\lambda \ otherwise. \tag{7}$$

Respectively that technical agent becomes fundamental one is:

$$\left(1-\delta_{t-1}^{C\to F}\right)=0{,}5-\lambda \ for\ A_t^C \rangle A_t^F\ ,$$
$$\left(1-\delta_{t-1}^{C\to F}\right)=0{,}5+\lambda \ otherwise. \tag{8}$$

Success (fitness of the rule) is represented by past profitability of the rules that are formalized as:

$$A_t^C=\left(\exp\left[P_t\right]-\exp\left[P_{t-1}\right]\right)D_{t-2}^C+dA_{t-1}^C \tag{9}$$

for the technical rules. And:

$$A_t^F=\left(\exp\left[P_t\right]-\exp\left[P_{t-1}\right]\right)D_{t-2}^F+dA_{t-1}^F \tag{10}$$

for the fundamental rules. Agents use most recent performance (at the end of A^C formula resp. A^F) and also the orders submitted in period $t - 2$ are executed at prices started in period $t - 1$. In this way the profits are calculated. Agents have memory, which is represented by the parameter d. Values are $0 \leq d \leq 1$. If $d = 0$ then agent has no memory, much higher value is, much higher influence the profits have on the rule fitness.

2.2 Extension of Original Model

Original model (Westerhoff, 2009) has (in our parameterization) tendency to stabilize itself in a long term – if the fundamental trading rules are overbearing the technical trading method, although the bubbles and the crashes occur, their values are going to be smaller because the price is targeting near the fundamental value and the volatility is going to be less too.

After introduction of the transaction cost influence on the price – the price is going up to the bubble while technical traders are overtaking the market. Then possible two scenarios can occur:

- Transaction costs value is low – the price starts to be falling according the fundamental traders' weight growth. In this moment volatility falls down and the market stabilizes.
- Transaction costs value is high – fundamental traders' weight = 0, the system destabilizes and the price grows without limit.

The value we assigned to transaction costs was 0.001. The price calculation has changed in this way:

$$P_{t+1}=\left(P_t+\alpha\left(W_t^C D_t^C+W_t^F D_t^F\right)+\alpha_t\right)+TC \tag{11}$$

Then we involved the risk into original model. The risk was implemented as a price risk percentage (*RP*) which decreases the price of an asset. It is generated each turn from given interval according uniform random distribution <0, 100>. So for risk influence the price formula has changed in this way:

$$P_{t+1}=\left(P_t+\alpha\left(W_t^C D_t^C+W_t^F D_t^F\right)+\alpha_t\right)*RP \tag{12}$$

Transaction costs were implemented in the same way as in previous simulations with adding constant value 0.01 to the price:

$$P_{t+1}=\left(P_t+\alpha\left(W_t^C D_t^C+W_t^F D_t^F\right)+\alpha_t\right)*RP+TC \tag{13}$$

The hypothesis can be transformed to the statement that transaction costs (Equation 13) will bring the same effect to the market as in the case of pure model without risk involvement. That means – with small amount of *TC* it will lead to the fundamental rules growth and simultaneously it will stabilize the market (Spišák and Šperka, 2011). Four types of simulations were done using original model (Equation 1), original model with TC (Equation 11), risk percentage involved in original model (Equation 12), and finally, risk together with transaction costs (Equation 13) to observe the difference.

3. Simulation Results

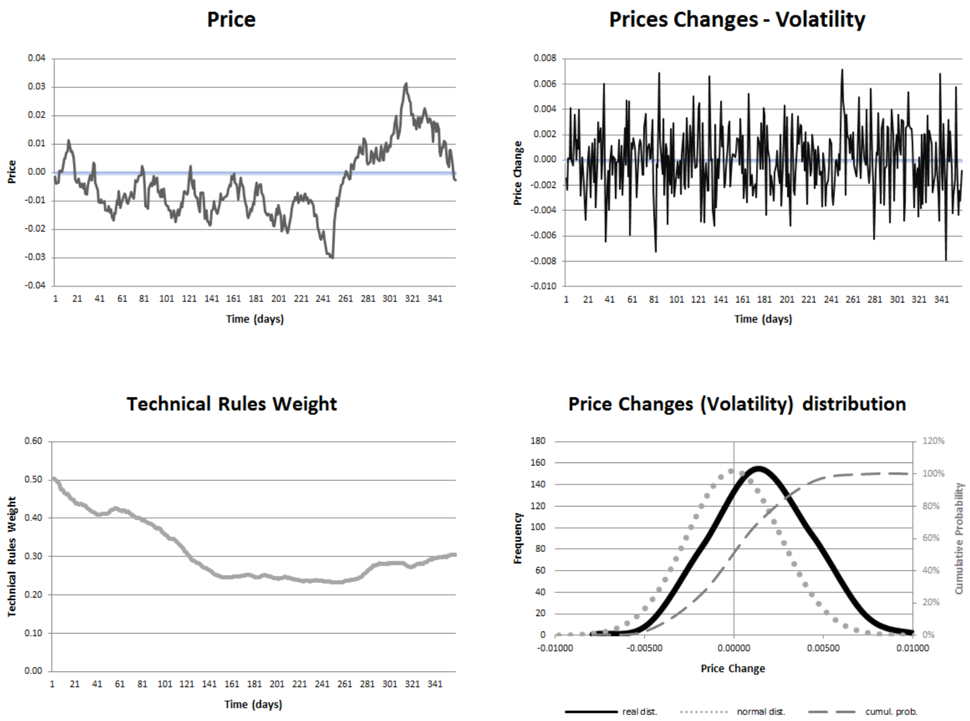
Simulation was done with 1 marketing agent and 500 trading agents. The rest of the parameters remained same as in original Westerhoff model (2009):

$a = 1$, $b = 0.05$, $c = 0.02$, $d = 0.95$, $\varepsilon = 0.1$, $\lambda = 0.45$, $\sigma\alpha = 0.0025$, $\sigma\beta = 0.025$, and $\sigma\gamma = 0.0025$

With these parameters the model is calibrated to the daily data. Number of ticks, resp. time steps is 360 days, which represents one year. Each generation (pure model, pure model + TC, risk only and risk with transaction costs) was done 31 times. Simulation results were aggregated to obtain more accurate view. Average data are shown in the graphs.

Results of the pure model simulation can be seen in the Figure 2. In all figures on the top left position the asset price values are depicted. Top right graph represents changes of the price in a time, which measures the volatility of the market. The bottom left graph shows the weights of technical trading rules (in a long time there is a tendency to prefer fundamental over technical trading rules). Bottom right graph includes the distribution of price changes compared with the normal distribution.

Figure 2: Results of the pure model simulation



Source: Own

In the next step we added TC to the model formalization. All the parameters are the same. Newly added TC is the constant value equal to 0.001. From the following graphs in Figure 3 we can declare that transaction costs firstly increase the price, but after that the price has stabilized. The volatility (price changes) is falling according to the changes to the technical traders' weights because the agents prefer the fundamental strategy. Results are depicted in the Figure 3.

Figure 3: Simulation of pure model with TC

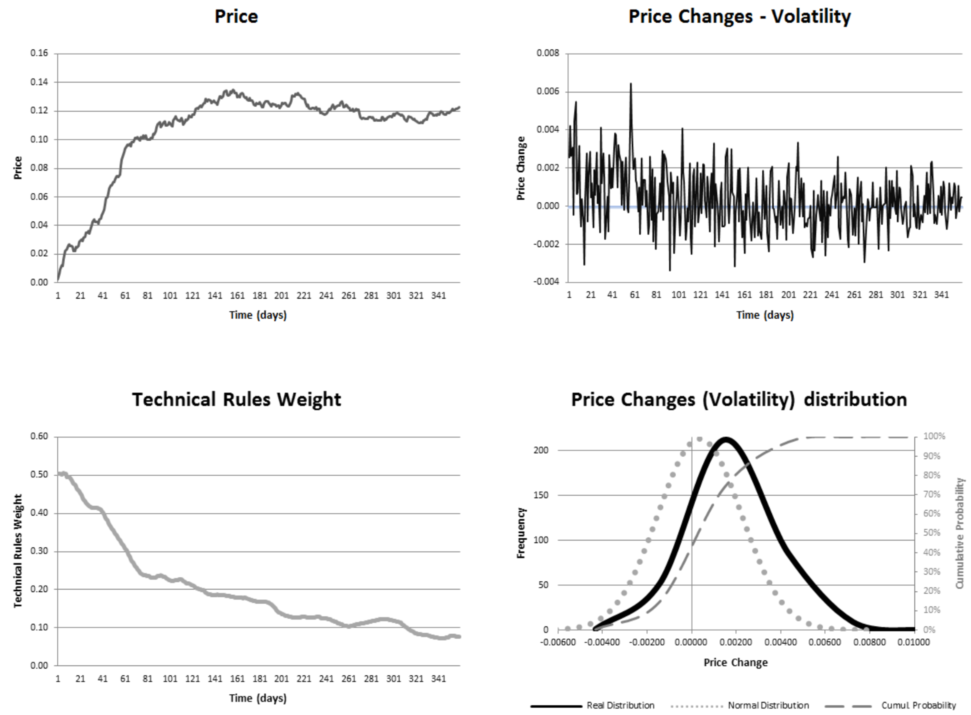


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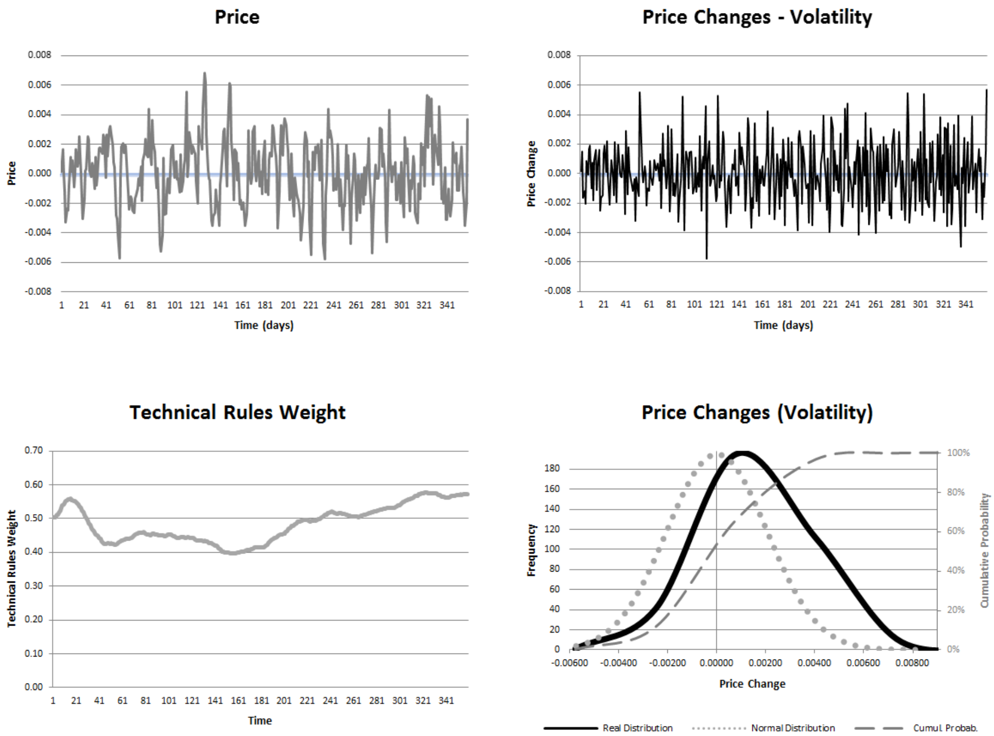
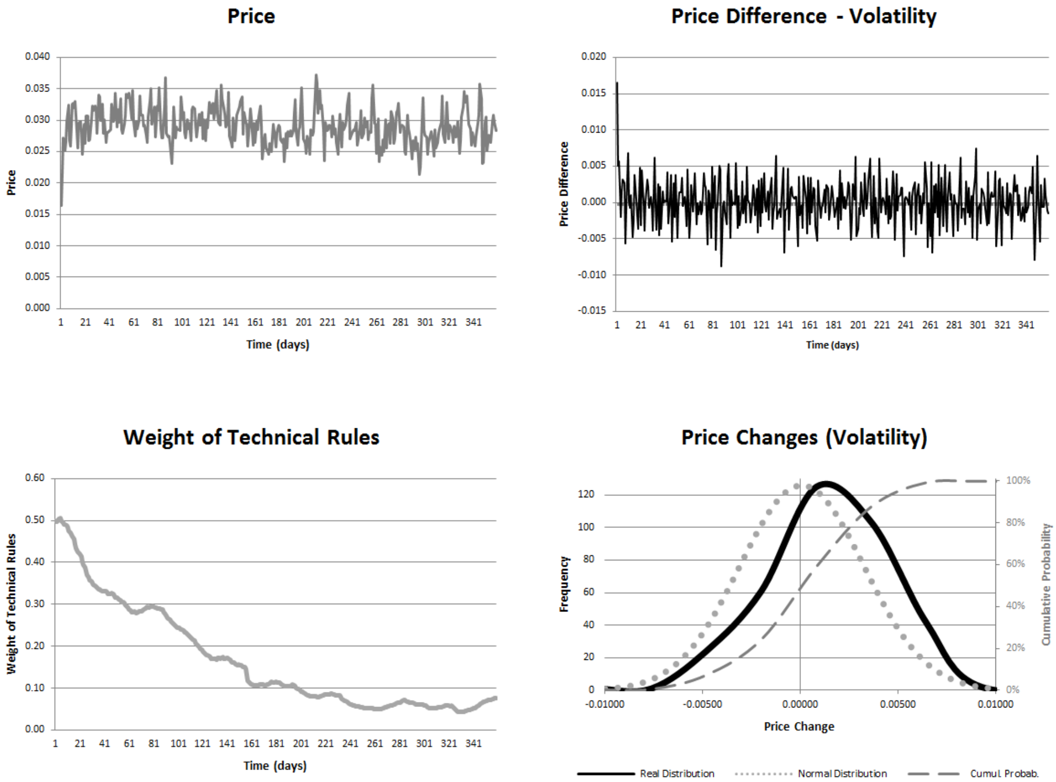
Figure 4: Simulation of risk involvement



Source: Own

In the next step, risk was involved into the model. Interval for price risk percentage values was decided as <0,100>. Results can be seen on the Figure 4. After that for stabilization of the model with risk TC were added. Value of the transaction costs was 0.01. The influence of the TC involvement on risk model was only partial. According to the hypothesis, the fundamental rules preferences have been growing. The price has only been growing at the beginning of simulation time. After the starting growth the price behavior became the same as in the model with risk. Also the volatility remained the same. We can conclude that the hypothesis wasn't fully fulfilled.

Figure 5: Simulation of risk + TC



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5. Conclusion

Agent-based simulation of financial market was introduced in this paper. Intelligent agents representing financial market participants followed fundamental and technical rules. The probability that agent switches from the fundamental to the technical behavior depends on the historic trend of asset's prices. The hypothesis for our research was based on our previous simulation results proving that transaction costs influence (Tobin tax) stabilizes the financial market. We involved the risk into original model and we supposed that transaction costs introduction would lead to the predominance of fundamental rules, which will automatically cause price lowering and market stability (measured by volatility in price changes).

The hypothesis was fulfilled only partially – the fundamental rules have growing tendency in time, but the prices and their differences are nearly the same in both simulations. We are not able to prove, that transactions costs have positive influence on the market stability when risk is involved in the model.

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References

BURIAN, J. (2010) *Multiagentní model transakčních nákladů na finančních trzích*. Praha: Vysoká škola ekonomická.

CONZELMANN, D., NORTH, M., BOYD, D., CIRRILLO, R., KORITAROV, V., MACAL, CH., THIMMAPURAM, T., VESELKA, T. (2004) *Simulating Strategic Market Behavior Using an Agent-Based Modeling Approach*. Result of a Power Market Analysis for the Midwestern United States, 6th IAEE European Energy Conference on „Modelling in Energy Economics and Policy".

EPSTEIN, J. M., AXTELL, R. (1996) *Growing Artificial Societies: Social Science from the Bottom Up*. Brookings Institution Press, MA, ISBN: 0-262-55025-3.

GALLOVA, Z., REPKOVA, I. (2011) Impact of Financial Crisis on the Czech Credit Market. In *Proceedings of the 6th International Scientific Symposium on Business Administration.* Karvina: Silesian University in Opava, pp. 38-48.

GONGOL, T. (2012) The Position of Financial Arbitrator among other Alternative Dispute Resolution. In STAVÁREK, D., VODOVÁ, P. (ed.) *Proceedings of the 13th International Conference on Finance and Banking*. Karviná: Silesian University in Opava, pp. 98-103.

HAYEK, F. A. (1949) *Individualism and Economic Order*. Routledge and Kegan Paul Ltd., London.

KAEGI, M. (2009) *Risk Analysis of Information Systems by Agent-based Modeling of Business Processes.* Disertation. Swiss Federal Institute of Technology. Zurrich.

LAW, A. M., KELTON, W. D. (2000) *Simulation Modeling and Analysis*. 3rd ed., McGraw-Hill: New York, 2000, ISBN 0070592926.
PRITSKER, A. A. B. (1995) *Introduction to Simulation and SLAM II*. Wiley: New York, ISBN 0470234571.

LOTE, R. (2007) *Agent Based Modeling of Electronical Markets to Analyze the Sustainability of Mutual Cooperation*. School of the University of Massachusetts. Undustrial Eingeneering and operations research, Master Theses. Paper 13.

MACAL, C. M., NORTH, M. J. (2006) Tutorial on Agent-Based Modeling and Simulation Part 2: How to Model With Agents, *Proceedings of the Winter Simulation Conference*, p. 73-83.

SALLACH, D. L., MACAL, C. M. (2001) Introduction: The Simulation of Social Agents. *Social Science Computer Review*, Sage Publications, Thousand Oaks, CA, vol. 19, no. 3, pp. 15-29, DOI 10.1177/089443930101900301.

ŞTEFANESCU, A., ŞTEFANESCU, L. (2013) An Intelligent Agents' Approach to Support the Management Decision Making Process in the Virtual Organization. AWERProcedia Information Technology & Computer Science. [Online]. 2013, 3, pp 1476-1482. *Proceedings of 3rd World Conference on Information Technology (WCIT-2012)*, Barcelona: University of Barcelona, Spain.

STOKLASOVÁ, R. (2012) Model of the Unemployment Rate in the Czech Republic. In: *Proc. 30th International Conference Mathematical Methods in Economics*. Part II. Silesian University in Opava, Karvina, Czech Republic, pp. 836-841, ISBN 978-80-7248-779-0.

SZAROWSKÁ, I. (2010) Theory and Practice of Tax Burden in the European Union. In STAVÁREK, D., VODOVÁ, P. (ed.) *Proceedings of the 12th International Conference on Finance and Banking*. Karviná: Silesian University in Opava, pp. 224-234. ISBN 978-80-7248-592-5.

ŠPERKA, R., SPIŠÁK, M. (2012) Tobin Tax Introduction and Risk Analysis in the Java Simulation. In: *Proc. 30th International Conference Mathematical Methods in Economics*. Part II. Silesian University in Opava, Karvina, Czech Republic, pp. 885-890, ISBN 978-80-7248-779-0.

TESFATSION, L. (2002) Agent-Based Computational Economics: Growing Economies from the Bottom Up. *Artificial Life*, Vol. 8, No.1, pp. 55-82, MIT Press, Cambridge, MA.

WESTERHOFF, F. (2009) *A Simple Agent-based Financial Market Model: Direct Interactions and Comparisons of Trading Profits*. Working Paper No. 61. Bamberg University (BERG Working Paper).
SPIŠÁK, M., ŠPERKA, R. (2011) Financial Market Simulation Based on Intelligent Agents – Case Study, *Journal of Applied Economic Sciences*, Volume VI, Issue 3(17), 2011, Romania, Print-ISSN 1843-6110.