Tobin tax introduction and risk analysis in the Java simulation

Roman Šperka[1], Marek Spišák[2]

Abstract. This paper deals with the agent-based simulation. The aim of the paper supported by the hypothesis is to prove positive impact of Tobin tax introduction together with the risk analysis on the stability of financial market. The core of the paper is the Java implementation of the multi-agent system being served as simulation framework. Multi-agent systems consist of a significant number of cooperating elements, so called intelligent agents. A multi-agent financial market model and simulation is 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 behaviour. 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.

Keywords: ABMS, simulation, Tobin tax, risk analysis, financial model.

JEL Classification: E37, E44, C53, C63, C90
AMS Classification: 68U20

1 Introduction

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 [4] 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 behaviour." He opposed mainly against collectivist theories which claim to be able to fully understand the social right, regardless of the individuals who constitute them. Hayek also elaborated on the theme of dispersed interactions between individuals. The basis for thinking about human society is the fact that no member can know more than a tiny part of society and therefore everything that goes into the decision-making are the immediate results that will have proceedings to the surroundings. 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 falls, is this idea the primary principle [8]. Agents, unlike classical equilibrium approach have not perfect information about all processes in the system.

No strict rules are conducted to the agents. They themselves select those practices that lead to the best results according to the success of strategies and rules. They are not looking for universal general rule. They are governed by a method that has proven in the environment under given conditions in the past. Multi-agent approach uses various scientific methods for introducing the adaptive behaviour of the program structures (e.g. [5]). The basic feature of complex adaptive systems is that their global properties can be easily derived from the characteristics of individual units (agents). Although each agent structure is simple, the behaviour of the system as a whole can be very difficult. A complex system is not the same as a chaotic system. Generally, a complex system tends to evolve away from both extremes - full of randomness on the one hand and absolute order on the other [6]. Multi-agent systems are based on the selection of behaviour rules that are subjectively optimal in certain environment for each agent functioning. Multi-agent system implemented through ABMS consists of two types of rules - spontaneous and created. The agent should be determined what their purpose is, what variable or group of variables to be monitored and optimized. On the other hand the way for reaching goals, is already left full of them.

[1] Silesian University in Opava, School of Business Administration in Karviná, sperka@opf.slu.cz
[2] Silesian University in Opava, School of Business Administration in Karviná, spisak@opf.slu.cz

Computational social science involves the use of ABMS to study complex social systems [3]. 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 [7]. Although many traits are shared, ABMS is differentiated from these approaches by its focus on finding the set of basic decision rules and behavioural interactions that can produce the complex results experienced in the real world [9]. ABMS tools are designed to simulate the interactions of large numbers of individuals so as to study the macro-scale consequences of these interactions [11]. 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.

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 [2] 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 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 able of agents behaviour investigation. Multi-agent system will be developed and managed as a simulation framework in JADE development platform (JAVA programming language [1]). This paper deals with the agent-based simulation of the Tobin tax introduction together with the risk analysis and their impact on the stability of financial market. The motivation 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 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 behaviour. 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. The aim of the paper supported by the hypothesis is to prove the positive influence of Tobin tax introduction on the stability of financial market. 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 description

The model developed by Frank Westerhoff [12] 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 instability.

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 relationship between them. The success of rules is represented by current and passed 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.

$$P_{t+1} = P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t \tag{1}$$

Where a is positive price adjustment coefficient, D^C are orders generated by technical angents 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 Figure 1. It is an IID[3] 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:

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

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:

$$D_t^F = c(F - P_t) + \gamma_t \tag{3}$$

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[4] . 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:

$$W_t^C = K_t/N \tag{4}$$

And the weight of fundamental traders:

$$W_t^F = (N - K_t)/N \tag{5}$$

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 behaviour with a probability K. Probability of transition is defined as $(1-\delta)$. Also there is a small probability ε that agent changes his mind independently. Transition probability is formalized as:

$$K_t \begin{cases} K_{t-1} + 1 \;\; with\,probability \;\; p_{t-1}^{+} = \dfrac{N - K_{t-1}}{N}\left(\varepsilon + (1-\delta)_{t-1}^{F\to C} \;\; \dfrac{K_{t-1}}{N-1}\right) \\ K_{t-1} - 1 \;\; with\,probability \;\; p_{t-1}^{-} = \dfrac{K_{t-1}}{N}\left(\varepsilon + (1-\delta)_{t-1}^{C\to F} \;\; \dfrac{N - K_{t-1}}{N-1}\right) \\ K_{t-1} \qquad with\,probability \;\; 1 + p_{t-1}^{+} - p_{t-1}^{-} \end{cases} \tag{6}$$

Where the probability that fundamental agent becomes technical one is:

$$(1-\delta)_{t-1}^{F\to C} = \begin{cases} 0.5 + \lambda \, for \; A_t^C > A_t^F \\ 0.5 - \lambda \, otherwise \end{cases} \tag{7}$$

Respectively that technical agent becomes fundamental one is:

$$(1-\delta)_{t-1}^{C\to F} = \begin{cases} 0.5 - \lambda \, for \; A_t^C > A_t^F \\ 0.5 + \lambda \, otherwise \end{cases} \tag{8}$$

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

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

[3] independent and identically distributed
[4] in our implementation F = 0

for the technical rules. And:

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

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 Previous simulations

From our previous simulations [10] was seen that original model which was implemented 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.

2.3 Extension of original model and hypothesis

The risk was implemented as a price risk percentage (RP) which is generated each turn from given interval according uniform random distribution[5]. So for risk influence the price formula has changed in this way:

$$P_{t+1} = (P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t) * RP \quad (11)$$

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

$$P_{t+1} = (P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t) * RP + TC \quad (12)$$

The hypothesis is that transaction costs (12) will bring the same effect to the market as in the case of pure model without risk involvement – with small amount of TC it will stabilize the market [10]. Two types of simulations were done using (11) and (12) – one only with risk percentage and the second one with transaction costs to see 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 Westernhoff model:

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

With these parameters the model is calibrated to the daily data. Number of turns, resp. time steps is 360 days, which represents one year. Each generation (risk only and risk with transaction costs) was done 25 times. Results were aggregated to obtain more accurate results. Average data were calculated.

Interval for percentage values was decided as <-1, 3>; when 1 (as 100 %) means not changed price. Results can be seen in the following graphs. In Figure 1 and 2 on the top left position the price values can be seen. Top right graph represents changes of the price in a time. The bottom left graph shows the weights of technical trading rules (in a long time there is a tendency to prefer fundamental than technical trading rules). Bottom right graph includes the distribution of returns (log price changes) compared with the normal distribution. Figure 1 shows the results in case of risk involvement into model. All four parts of the figure describe current situation on the market. Volatility of prices is clearly visible. There is possibility that prices can change rapidly in both directions. In 2008 felt the prices significantly down and the market was destabilized. In order to prevent to the destabilization situation, we suggest Tobin tax implementation into the system.

[5] None single outcome has higher probability than others.

Figure 1 Results of risk involvement simulation (source: own)

We outcome from this situation and the Tobin tax implementation into the system was done. Tobin tax was involved in the model in the form of transaction costs. The value of the transaction costs was set to TC = 0.001. Results can be seen in the figure 2. The parts of the figure represent the same phenomena as in the above paragraph. Three parts of the figure seem to be same as in the risk involvement graph. Only one part has changed. In the long term the fundamental rules overcome the technical rules. That is one sign of the financial market stabilization. To confirm the hypothesis the price changes should be lower. This was not proven. So the hypothesis can be fulfilled only partially.

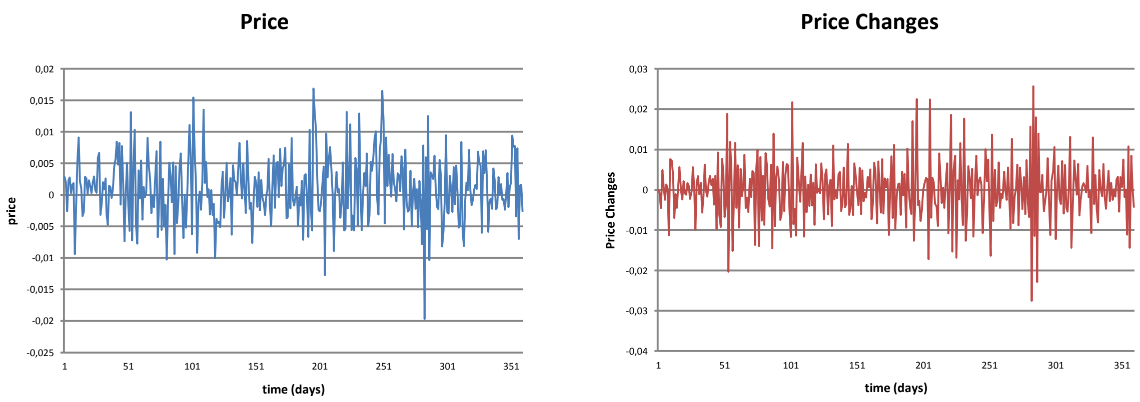

Figure 2 Results of risk involvement simulation with TC (source: own)

4 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 behaviour 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 will focus on the risk and parametrization of the model in our next research steps in order to prove that Tobin tax has positive impact on the stability of financial market.

References

[1] Bellifemine, F., Caire, G., and Trucco, T.: *Jade Programmer's Guide. Java Agent Development Framework*, 2010. Available from WWW:<http://jade.tilab.com/ doc/programmersguide.pdf>.
[2] Burian, J.: *Multiagentní model transakčních nákladů na finančních trzích*. VŠE Praha, 2010. Available from WWW: < http://www.eldar.cz/honza/articles/burian_ace_fin_market_tc.doc >
[3] Epstein, J. M., and Axtell, R.: *Growing Artificial Societies: Social Science from the Bottom Up*. Brookings Institution Press, MA, 1996, ISBN: 0-262-55025-3.
[4] Hayek, F.A.: *Individualism and Economic Order*. Routledge and Kegan Paul Ltd., London, 1949.
[5] Holland, J.H.: *Adaptation in Natural and Artificial Systems*. The University of Michigan, 1975.
[6] Kochugovindan, S., and Vriend, N.J.: *Is the Study of Complex Adaptive Systems Going to Solve the Mystery of Adam Smith's 'Invisible Hand'?* The Independent Review, 3, No.1, 1998, 53-66.
[7] Law, A. M., and Kelton, W.D.: *Simulation Modeling and Analysis*. 3rd ed., McGraw-Hill: New York, 2000, ISBN 0070592926.
[8] Macal, C. M., and North, M. J.: Tutorial on Agent-Based Modeling and Simulation Part 2: How to Model With Agents. *Proceedings of the Winter Simulation Conference*, 2006, 73-83..
[9] Sallach, D. L., and Macal, C. M.: *Introduction: The Simulation of Social Agents*. Social Science Computer Review, Sage Publications, Thousand Oaks, CA, Fall 2001, vol. 19, no. 3, DOI 10.1177/089443930101900301, 15-29.
[10] Spišák, M., and Šperka, R.: *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.
[11] Tesfatsion, L.: *Agent-Based Computational Economics: Growing Economies from the Bottom Up*. Artificial Life, Vol. 8, No.1, MIT Press, Cambridge, MA, 2002, 55-82.
[12] Westerhoff, F.: *A simple agent-based financial market model: direct interactions and comparisons of trading profits. Working Paper No. 61*. Bamberg University (BERG Working Paper Series on Government and Growth), January 2009.