FINANCIAL MARKET SIMULATION BASED ON INTELLIGENT AGENTS – CASE STUDY

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Abstract:

We implement an agent-based financial market model simulation in which 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 is studied, which can be increased by the off-market regulation (for example in the form of taxes) on market stability, the overall volume of trade and other market characteristics.

Keywords: agent-based, financial market, netLogo, direct interactions, technical and fundamental analysis, simulation

JEL Classification: G12; G14; G15; C63; C88

1. Introduction

This paper describes a multi-agent model of the transaction costs influence on the financial market. 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 that can lead to the reduced growth or even to the recession.

Tobin tax was never implemented. Against introducing a Tobin tax, however there are number of arguments. First, it would be very difficult to implement, since it would have to be introduced in sync throughout the world, because otherwise the market would be relocated to the tax-free exchange. Another argument is to reduce the volume. Finally, some authors argue that financial speculators, whose activity would be substantially reduced, are doing useful work, for example, they seek new possibilities to invest in emerging markets. There are also opinions that stability problems can be solved by improving the macroeconomic policies of central banks.

The model described here, however, need not be interpreted as a model for the introduction of taxes, but in general, as a model of the transaction costs influence on the market. The aim of the model described in this article is to explore the dependence market stability to the extent of transaction costs.

This paper is structured as follows. Section 2 briefly informs about the behaviour on real financial markets and introduces the agent-based methods for modelling and simulation. In section 3 the original agent-based model of financial market is presented. In section 4 we enhance the original model with transaction costs. Section 5 presents the original simulation results of the agent-based model of financial market.

2. The Use of Agent-based Methods for Modelling and Simulation the Behaviour of Real Financial Markets

The behaviour of real financial markets shows some significant deviations from the efficient-market hypothesis, which argues that the market price reflects all information on the fair value of traded assets and should not deviate from it. In fact, the market price often differs from the fair value of assets, which is reflected especially in the so-called market bubbles (Ilie 2011). Market bubble is an artificial overvaluation of assets due to excessive demand, or on the other hand it is the market collapse due to the oversupply of the assets. Efficient-market hypothesis is according to (Schleifer 2000) based on three basic assumptions: the investors are able to rate the assets with unlimited rationality. If some investors are not rational, their purchases are random and therefore they cancel each other out, and finally the influence of irrational investors on the price of the assets is eliminated by rational agents. (Burian 2010).

The model described in this article is based on the agent-based model of financial market (Westerhoff, 2009), which, like many similar models (Brock and Hommes 1997, 1998; Gonçalves 2003; Kirman 1991, 1993; Lux 1998; Lux and Marchesi 1999) describes some typical characteristics of the real market. An agent-based model is a computerized simulation of a number of decision-makers (agents) and institutions, which interact through prescribed rules (Vymetal and Sperka, (2011). The agents can be as diverse as needed - from consumers to policy-makers and Wall Street professionals - and the institutional structure can include everything from banks to the government. Such models do not rely on the assumption that the economy will move towards a predetermined equilibrium state, as other models do. Instead, at any given time, each agent acts according to its current situation, the state of the world around it and the rules governing its behaviour. An individual consumer, for example, might decide whether to save or spend based on the rate of inflation, his or her current optimism about the future, and behavioural rules deduced from psychology experiments. The computer keeps track of the many agent interactions, to see what happens over time. Agent-based simulations can handle a far wider range of nonlinear behaviour than conventional equilibrium models. Policy-makers can thus simulate an artificial economy under different policy scenarios and quantitatively explore their consequences.

The cure for macroeconomic theory, however, may have been worse than the disease. During the last quarter of the twentieth century, 'rational expectations' emerged as the dominant paradigm in economics. This approach assumes that humans have perfect access to information and adapt instantly and rationally to new situations, maximizing their long-run personal advantage. Of course real people often act on the basis of overconfidence, fear and peer pressure - topics that behavioural economics is now addressing. (Farmer and Foley 2009)

But there is a still larger problem. Even if rational expectations are a reasonable model of human behaviour, the mathematical machinery is cumbersome and requires drastic simplifications to get tractable results. The equilibrium models that were developed, such as those used by the US Federal Reserve, by necessity stripped away most of the structure of a real economy. There are no banks or derivatives, much less sub-prime mortgages or credit default swaps - these introduce too much nonlinearity and complexity for equilibrium methods to handle. Agent-based models could help to evaluate policies designed to foster economic recovery.

We may use agent-based methods in the case of the financial market, which is a relatively balanced market (supply roughly coincides with the demand) with bubbles and busts. Furthermore, in contrast to the efficient-market hypothesys assumptions is more realistic to assume that (Burian 2010):

• Agents are limited only rational. They do not have all information or they are not able to interpret it correctly.

• Agents are heterogeneous. They react with varying sensitivity to the reports of the market developments and affect them differently strong random factors that influence their decisions.

• Agents make decisions influenced by the opinions of their close colleagues.

The model, which we describe in this paper, is based on these assumptions.

3. Original Model

The model developed by Frank Westerhoff (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**, whose 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**, who 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 they are discussing their trading performance. One agent can be persuaded by the other to change his trading method, if his rules relative success is less than the others one. Communication is direct talk one agent with other. Talking agents meets randomly – there is no special relationship between them. The success of rules is represented by current and passed myoptic profitability. It is very important to mention, that model assumes traders ability to define the fundamental value of assets and they are 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 respective fundamental rules. They are reflecting current ratio between the technical and fudamental agents. α brings the random term to the **Error! Reference source not found.**. It is an IID[1] 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 aproximation of them. So if the price is below the fundamental value – the assets are bought and vice versa – orders according fundamentalists are formalized

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

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[2]. 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 (4)

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

and the weight of fundamental traders

[1] independent and identically distributed

[2] in our implementation F = 0

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

Two traders meet at each step and they are discussing 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 $(1-\delta)$. Also there is a small probability ε that agent changes his mind independently. Transition probability is formalized as

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

where the probability that fundamental agent becomes technical one is

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

respective that technical agent becomes fundamental one is

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

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

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

for the technical rules and

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

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 myoptic profits are calculated. Agents have memory – which is represented by the parameter d. Values are $0 \le d \le 1$. If d = 0 then agent has no memory, much higher value is, much higher influence the myoptic profits have on the rule fitness.

Implementation was done in NetLogo which author is Uri Wilensky – vide (Wilensky 1999). NetLogo is the environment for modeling problems or systems which have natural or social character. Its development has started in 1999 and is still in progress in Center for Connected Learning and Computer-Based Modeling in Northwestern University in Chicago (USA).

The tool is programmable – it is a variant of Logo language, into which the agent support was added. Because of the language the work with it is intuitive and easy[3]. It is not necessary to have very deep programmer knowledge and skills to be able to make simulations and visualize them. In Figure 1 it is possible to see one simulation process with its results. In the left part there are parameters (for values see the section 5) in the middle we can see the evolution of the key values (log price, returns as their changes, weights of technical traders) and in the right there is graphically shown the rate between fundamental (black) and technical traders (yellow).

[3] Logo is one of languages, which are used for thinking education, is used for children's programming learning

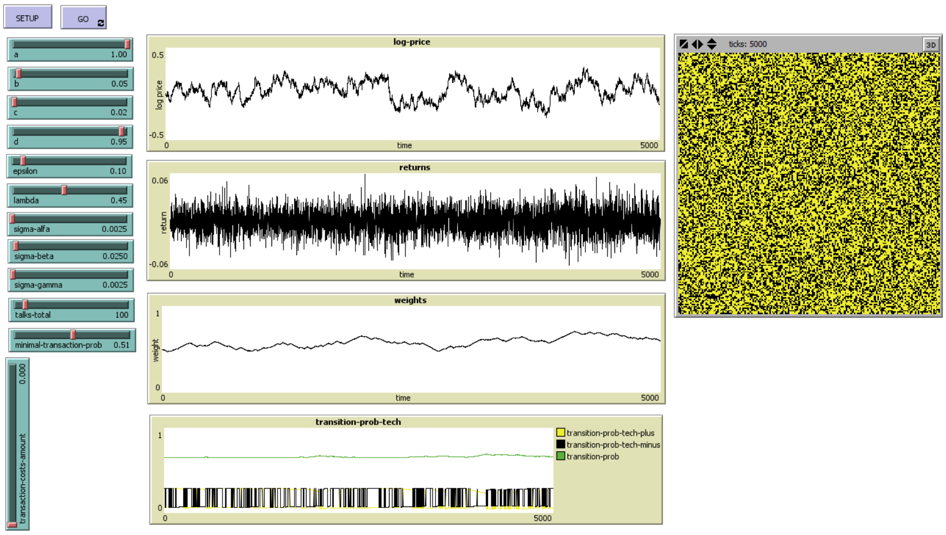

Figure 1. Results of the simulation process.

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4. Enhancement of the Model with Transaction Costs

The aim of the model is to investigate the influence of the transaction costs on the market stability (which is measured by the price volatility – much more stable the market is, much less are price differences in a time). The entrance of transaction costs (TC) – e.g. a tax will have direct impact on the asset price. The model was little changed to adopt also this aspect into price. So the price is composed in this way:

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

Where TC is a value of the transaction costs, which is constant during all the simulation.

While the tax is out-of trade factor, all the agents will be affected in the same way. Generally there can be also different transaction costs than taxes – e.g. information obtaining costs.

The TC increase has following results:

- the price increase will stimulate technical rules usage, it's influence on the expected future profit opportunities (as the fundamental value of the asset) is irrelevant – they depend on the company state, rather than on transaction costs
- in a short time, the price growth will attract technical traders, but after the realized profits will fall down and the fundamental traders will start to dominate, it will lead to the market stabilization (price changes are falling – volatility of price is lower)

5. Simulation Results

To be more accurate, 20 simulations were processed, averaged values are being plotted in the result graphs.

5.1 Simulation in original model

Parameterization of the model was kept from original parameterization made by Westernhoff, only the number of agents (N) was set to 10,000 to obtain more relevant results. The parameters are:

$$a = 1, b = 0.05, c = 0.02, d = 0.95, \varepsilon = 0.1, \lambda = 0.45, \sigma^{\alpha} = 0.0025, \sigma^{\beta} = \\ = 0.025, \text{ and } \sigma^{\gamma} = 0.0025 \qquad (12)$$

With these parameters the model is calibrated to the daily data. Number of turns, resp. time steps is 5000 days, which presents more than 13 and half of year. (Westerhoff 2009) found that growing number of agents reduces the model dynamicity and the volatility of price, while agents behavior is tending to be fundamental. This can be reduced by adding more communication turns. We have decided to give opportunity to talk to 1 %, which has positive influence on the model dynamicity.

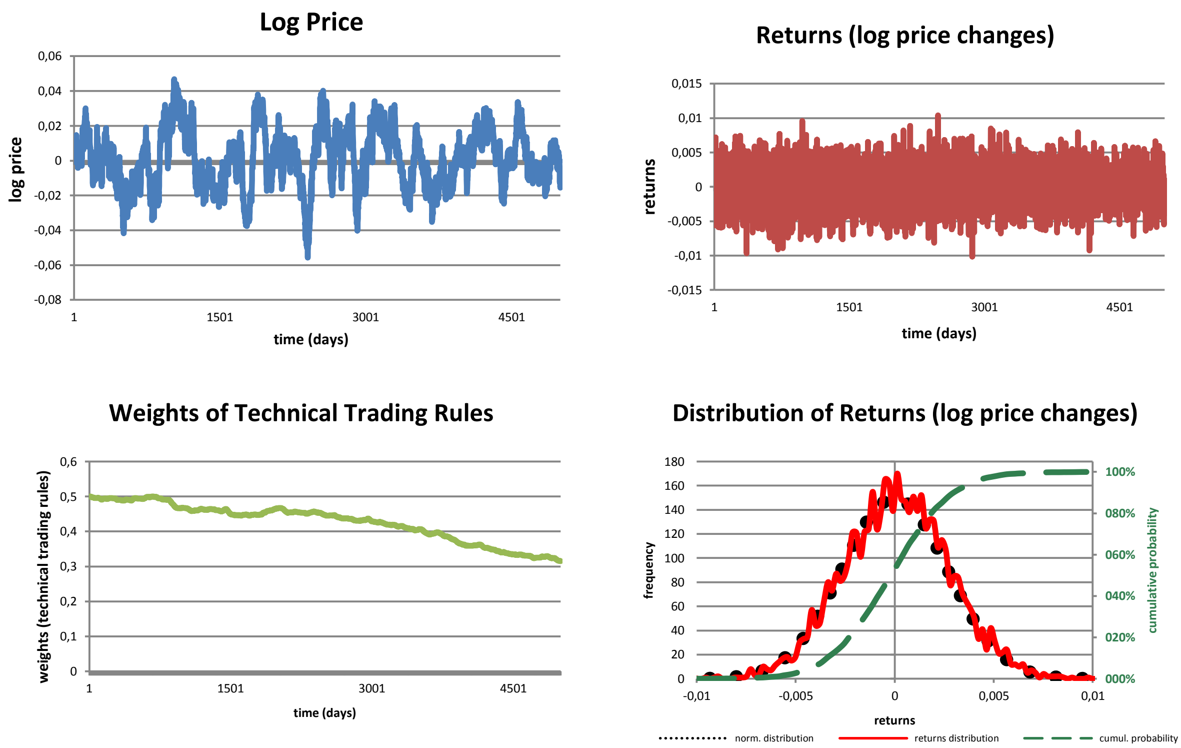

Figure 2. Simulation results in original model.

Source: own

In Figure 2 on 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 (which are log price changes) compared with the normal distribution.

5.2 Simulation with transaction costs

All the parameters stayed the same. Newly added TC is the constant value equal to 0.015. From the following graphs in Figure 3 is possible to see, that transaction costs have influence on the model – the price is growing in a short time, but in longer scope is falling. The technical weights evolution is similar – in a short time is growing, but after is starting to fall – as the agents prefer the fundamental strategy. With more fundamental traders the market stabilizes – which is readable from the returns (volatility of price changes is falling).

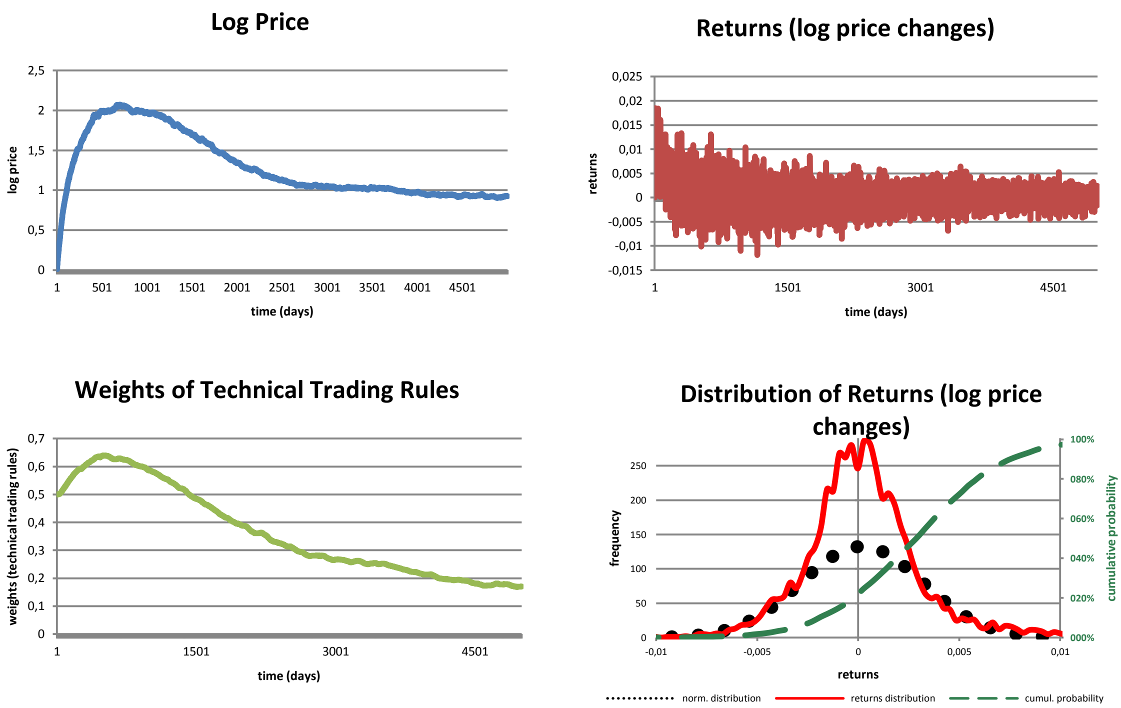

Figure 3. Simulation results with transaction costs.

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Big surprise was the last set of simulations. All the parameters remained the same; only the TC was doubled and became the constant value equal to 0.03. The higher value of TC made the model destabilization – technical traders rules won (weight = 1) and the price was growing without limit. Figure 4 demonstrates the contradictory effect on the market – instead of the stabilization, the market started to be unstable.

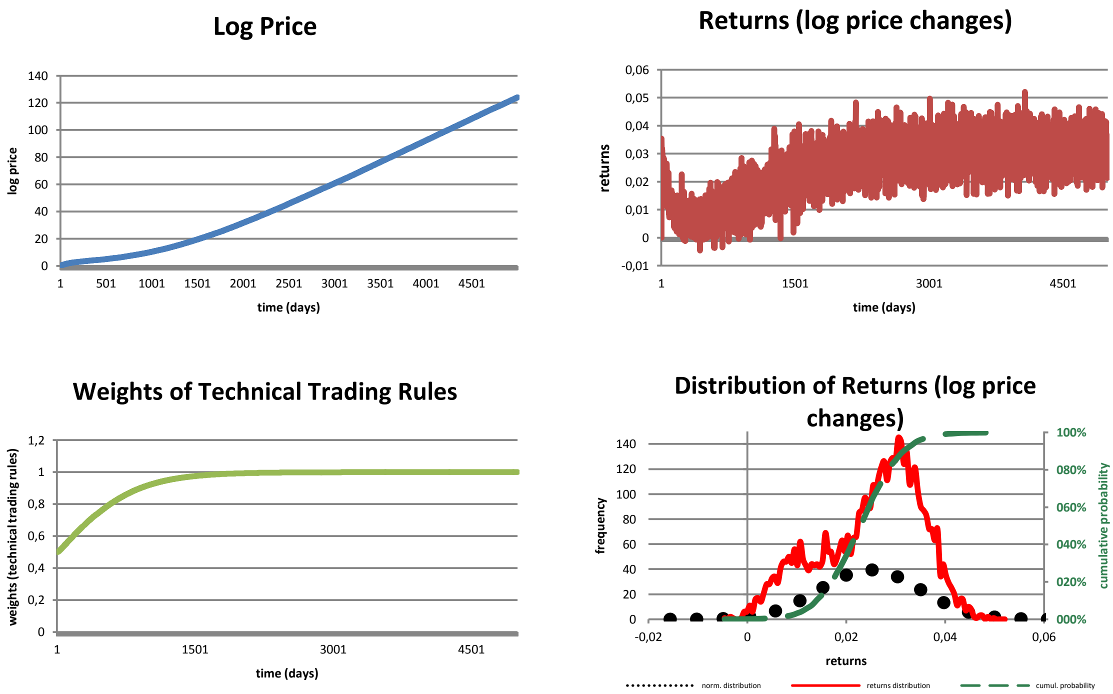

Figure 4. Simulation results with higher transaction costs.

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6. Conclusion

The agent financial model which was implemented (Westerhoff 2009) has (in our parameterization) tendency to stabilize itself in a long term – if the fundamental trading rules are overbearing the 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.

Once there is introduced the transaction cost influence on the price – the price is going up to the bubble while technical traders are overtaking the market, but the price starts to be falling according to the technical analysis growth. In this moment volatility falls down and the market stabilizes. The problem is the value of the transaction costs – as was seen in very last simulation, if is too high, the system destabilizes and the price grows without limit.

7. Acknowledgments

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