MULTI-AGENT SIMULATION OF FINANCIAL MARKET WITH TRANSACTION COSTS INFLUENCE

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Abstract: *We implement a multi-agent 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.*

Introduction

Simulation of financial market is a new fast growing research area with two primary motivations. The first is the need to provide a development platform for the ever increasing automation of financial markets. The second is the inability traditional computational mathematics to predict market patterns that result from the choices made by interacting investors in a market.

The market participants in our multi-agent model use technical and fundamental analysis to assess financial markets. Multi-agent financial market models have a strong empirical foundation. This paper firstly defines how financial market participants may select their trading rules, secondly describes a multi-agent model of the transaction costs influence on the financial market. We do this by using and extending the original model developed by Frank Westerhoff [12]. This model recombines a number of building blocks from three known agent-based financial market models.

In the first model [1] and [2] a continuum of financial market participants endogenously chooses between different trading rules. The agents are rational in the sense that they tend to pick trading rules which have performed well in the recent past, thereby displaying some kind of learning behavior. The performance of the trading rules may be measured as a weighted average of past realized profits, and the relative importance of the trading rules is derived via a discrete choice model. Contributions developed in this manner are often analytically tractable. Moreover, numerical investigations reveal that complex endogenous dynamics may emerge due to an ongoing evolutionary competition between trading rules. In such a setting, agents interact only indirectly with each other: their orders have an impact on the price formation which, in turn, affects the performance of the trading rules and thus the agents' selection of rules. Put differently, an agent is not directly affected by the actions of others.

In Kirman [6] and [7] an influential opinion formation model with interactions between a fixed number of agents was introduced. Agents may hold one of two views. In each time step, two agents may meet at random, and there is a fixed probability that one agent may convince the other agent to follow his opinion. In addition, there is also a small probability that an agent changes his opinion independently. A key finding of this model is that direct interactions between heterogeneous agents may lead to substantial opinion swings. Applied to a financial market setting, one may therefore observe periods where either destabilizing technical traders or stabilizing fundamental traders drive the market dynamics. Agents may change rules due to direct interactions with other agents but the switching probabilities are independent of the performance of the rules.

The models of Lux [8] and Lux and Marchesi [9] also focus on the case of a limited number of agents. Within this approach, an agent may either be an optimistic or a pessimistic technical trader or a fundamental trader. The probability that agents switch from having an optimistic technical attitude to a pessimistic one (and vice versa) depends on the majority opinion among the technical traders and the current price trend. For instance, if the majority of technical traders are optimistic and if prices are going up, the probability that pessimistic technical traders turn into optimistic technical traders is relatively high. The probability that technical traders (either being optimistic or pessimistic) switch to fundamental trading (and vice versa) depends on the relative profitability of the rules. However, a comparison of the performance of the trading rules is modeled in an asymmetric manner. While the attractiveness of technical analysis depends on realized profits, the popularity of fundamental analysis is given by expected future profit opportunities. This class of models is quite good at replicating several universal features of asset price dynamics.

The Westerhoff [12] model recombines key ingredients of the three aforementioned approaches to come with a simple model that is able to match the stylized facts of financial markets. Direct interactions between a number of agents is considered. To avoid asymmetric profit measures a fitness function is defined. The attractiveness of a rule is approximated by a weighted average of current and past myopic profits. We extended this model with transaction costs influence.

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 [3] 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.

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 paper is to explore the dependence market stability to the extent of transaction costs.

This paper is structured as follows. Section 1 briefly informs about the behaviour on real financial markets and introduces the agent-based methods for modelling and simulation. In section 2 the original agent-based model of financial market is presented. In section 3 we enhance the original model with transaction costs. Section 4 presents the original simulation results of the agent-based model of financial market.

1 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. 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 [10] 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. [3]

The model presented in this paper 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 [11]. 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. [4]

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 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 hypothesis assumptions is more realistic to assume that [3]:

- 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 described in this paper is based on these assumptions.

2 Original Model

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**, 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 agents 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 fundamental agents. α brings the random term to the Fig. 1. It is an IID[20] normal random variable with mean zero and constant standard deviation σ^α.

As was already said, technical analysis extrapolates the 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 the 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

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

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[21]. 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 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 κ. 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

[20] independent and identically distributed
[21] in our implementation F = 0

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

where the probability that fundamental agent becomes technical one is

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

respective that technical agent becomes fundamental one is

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

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

$$A^C_t = (\exp[P_t] - \exp[P_{t-1}])D^C_{t-2} + dA^C_{t-1} \tag{9}$$

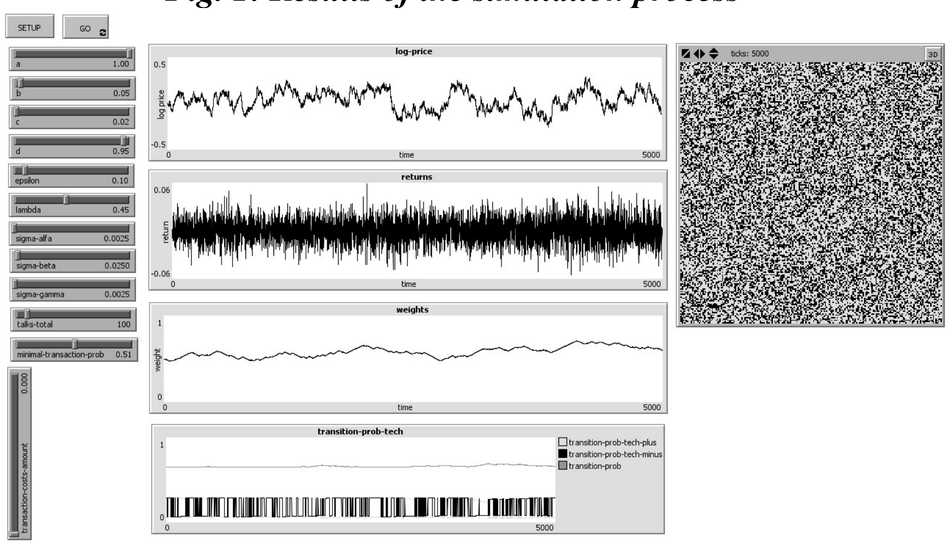
for the technical rules, and

$$A^F_t = (\exp[P_t] - \exp[P_{t-1}])D^F_{t-2} + dA^F_{t-1} \tag{10}$$

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 [13] – vide. NetLogo is the environment for modelling 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 Modelling in Northwestern University in Chicago (USA).

Fig. 1: Results of the simulation process



Source of data: Authors

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. It is not necessary to have very deep programmer knowledge and skills to be able to make simulations and visualize them. In Fig. 1 it is possible to see one simulation process with its results. In the left part there are parameters (for values see the section 4) 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 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, its 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).

4 Simulation Results

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

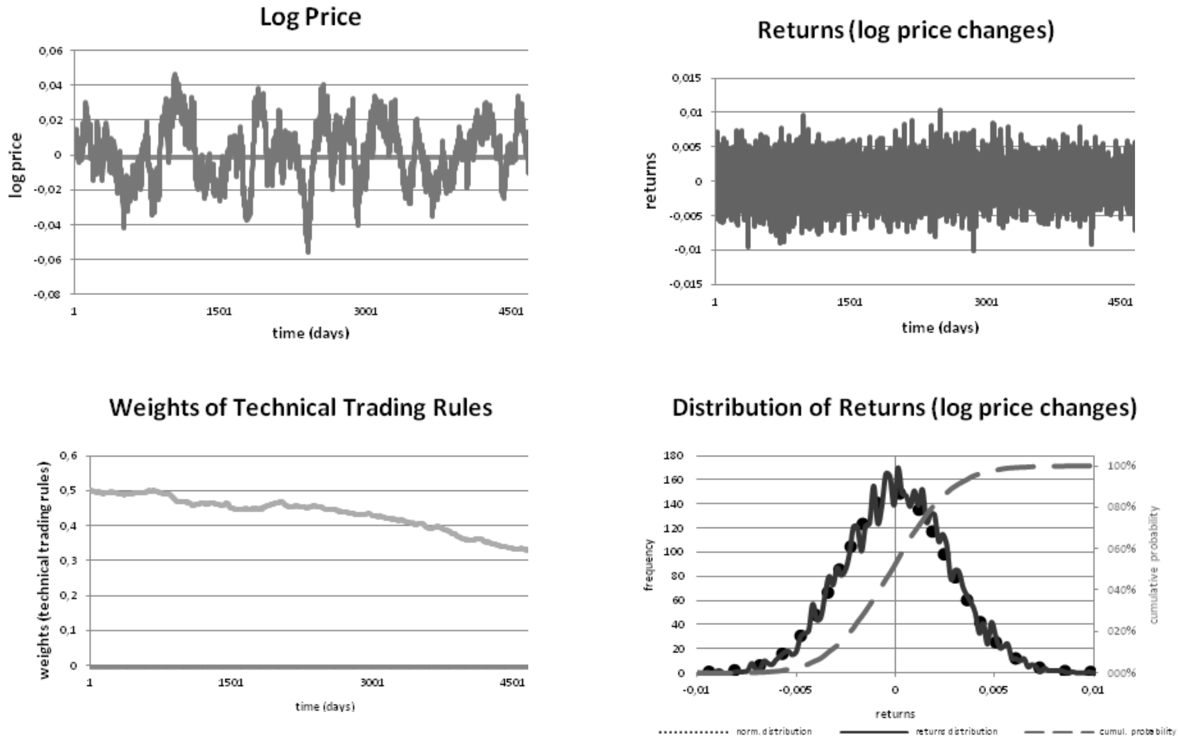
4.1 Simulation in original model

Parameterization of the model was kept from original parameterization made by Westerhoff [12], only the number of agents (N) was set to 10,000 to obtain more relevant results. The parameters are:

$a = 1$, $b = 0.05$, $c = 0.02$, $d = 0.95$, $\varepsilon = 0.1$, $\lambda = 0.45$, $\sigma\alpha = 0.0025$, $\sigma\beta = 0.025$, and $\sigma\gamma = 0.0025$ (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 [12] found that growing number of agents reduces the model dynamicity and the volatility of price, while agents behaviour 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.

Fig. 2: Simulation results in original model



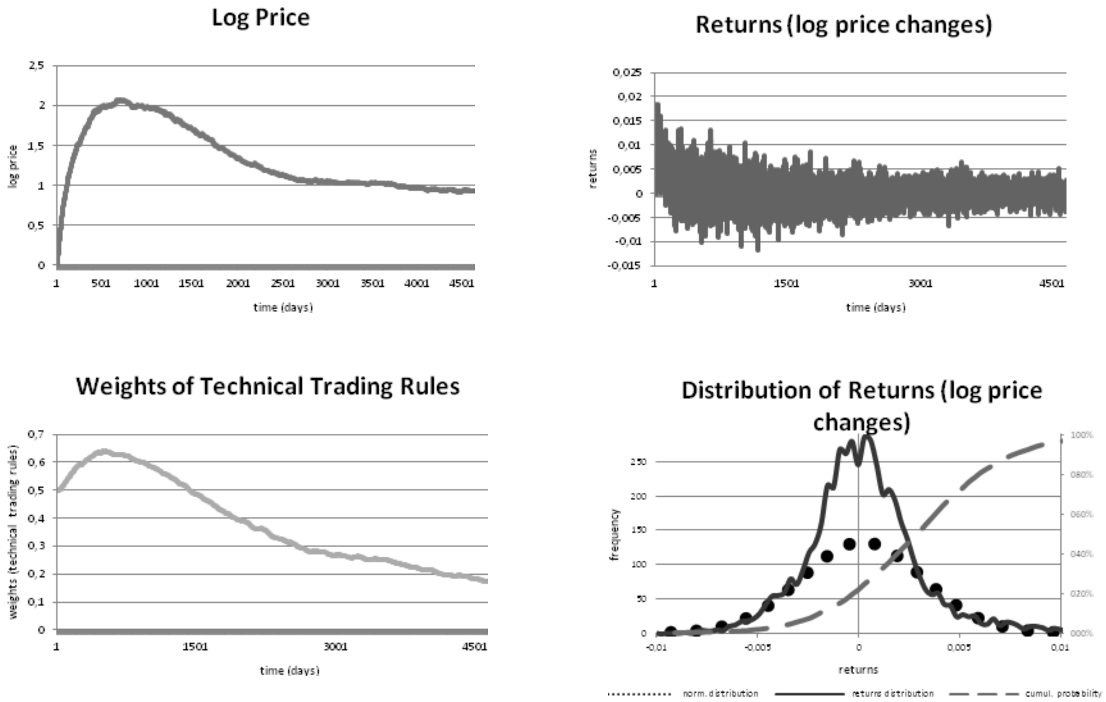
Source of data: Authors

In Fig. 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.

4.2 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 Fig. 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).

Fig. 3: Simulation results with transaction costs



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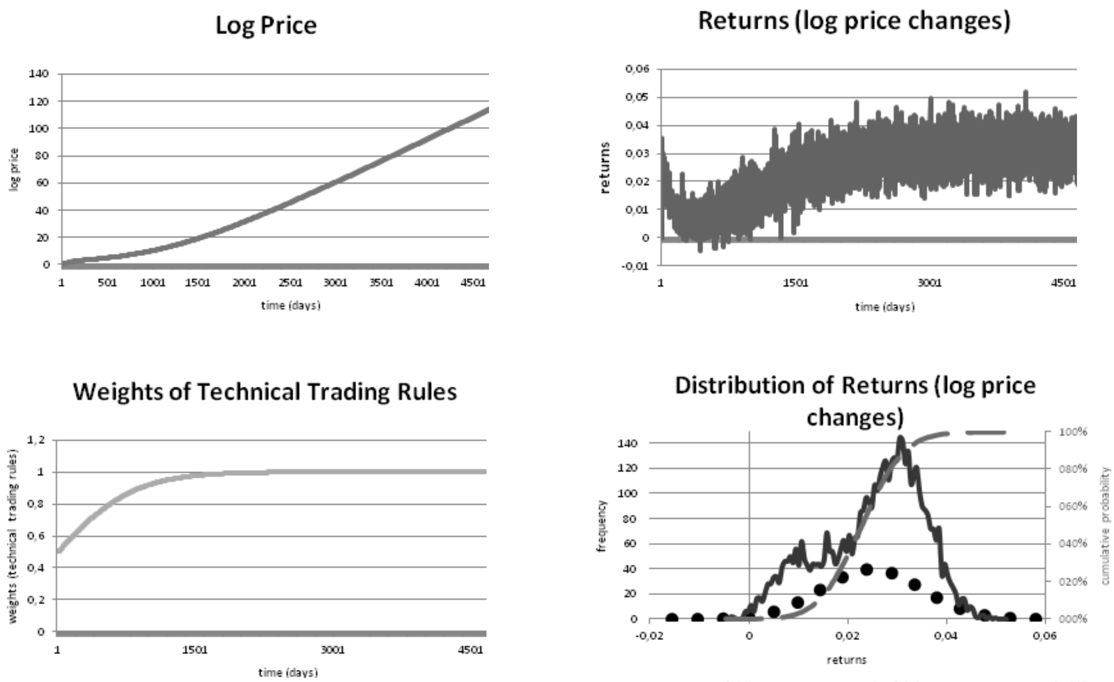
We achieved different results with the last set of simulations. All the parameters remained the same; only the TC was doubled and became the constant value equal to 0.03. The higher value of TC made the model destabilization – technical traders rules won (weight = 1) and the price was growing without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

Fig. 4: Simulation results with higher transaction costs



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Conclusion

The multi-agent financial model which was implemented in this paper 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. Different results are achieved with higher 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.

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