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The effect of exchange rate volatility on the transitional behavior of brokers: A perspective from Knowledge-driven Agent-based modeling with Software Simulation

P. KHUWAJA[++], S. A. KHOWAJA, S. ZARDARI[**], I. A. ISMAILI[*++]

Institute of Business Administration, University of Sindh, Jamshoro

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Abstract: The advancement in computational capabilities has escalated the use of agent-based simulations for the applications related to natural sciences. It brings a kind of rational expectation and local intelligence to decision support system. This kind of modeling allows us to simulate the behavior and analyze the outcome with acceptable certainty which cannot be performed otherwise in real-world settings. The popular data-driven approaches can be applied if the data is available, however, with unavailability of ground truth, the method fails to produce any outcome. On the other hand, knowledge-driven rules can perform simulation based on the domain knowledge and rules defined for the agent's behavior which in turn helps the model to reach a certain conclusion. To prove the applicability of simulation in such dynamic environments we consider a case study of the place where buyers and sellers exchange securities. In this paper, we implement an agent-based simulation for exhibiting the behavior of brokers in the suchtrading. Agents in the model determine their speculative investment positions using fundamental and technical trading rules. An agent can change its behavior towards the usage of rules based on the speculations and interactions with other agents. In this model, we have added the exchange volatility rate to the log-linear value model and added one more agent i.e., idle broker. The main aim of this study is to analyze the behavior of agents involve in the trading with unfavorable security conditions and the impactof such conditions on the current value and the transitional behavior of agents i.e., change in the probability of switching of one agent into another. The simulation of the model shows that exchange rate volatility significantly impacts the current value as well as the transitional behavior of the agents.

Keywords: Transitional Behavior, NetLogo, Fundamental and Technical Brokers, Agent-based methods, Simulation.

1. INTRODUCTION

The simulation modeling of natural science and econometrics applications is an escalating research area for two major reasons. First there is a dire need of automation software or architectures that can handle the increasing complexity of the application of interest. The second is the modeling of behavior and their interactions in the simulation model (Macal and North, 2005). In an efficient exchanging place, the need for demonstrating of such behavior arises due to the inability of traditional analytical and computational methods to extract meaningful information from the simulated patterns. Recent advances in modeling languages allow us to create multi-agent based models (in our case modeling the bourse market behavior) and to perform fundamental and technical analysis for their assessment (Spišák and Šperka, 2011)(Vymetal and Sperka, 2011; Wooldridge, 2009). Several development platforms use behavior modeling for sophisticated methods to ease the analysis of agent behavior and its impact on the target environment. It gives the researcher scalable environment and the flexibility to add more variables without changing the existing model. This paper deals with the trading rules of (BMM) with respect to different nature of participants. It takes into account the transaction cost as proposed by previous studies (Šperka and Spišák, 2013)but also adds exchange volatility linked to the security condition of the environment and how it affects the stability of the BMM. An existing model developed by Frank Westerhoff (Westerhoff, 2010) have been employed in this research. We have extended this model by combining a number of building blocks from four known multi-agent models on the similar theme.

(Brock and Hommes, 1997, 1998) highlighted the interaction of agents in trading environment using different trading rules. The participants tend to adopt the trading rules having good performance in previous iterations, which leads to a competitive learning behavior among agents. The weighted average of realized profits was set to be the assessment criteria for determining the performance of trading rules. The discrete choice model was employed to derive the importance of trading rules. The participants in this model are affected by the actions of other agents as they can indirectly interact with each other. In this way, the value formation can be influenced by the interaction of agents and also the behavior is easily controllable.

(Kirman, 1991, 1993) focused on the opinion formation model between the agents. The work mainly highlighted the view of agents that they hold at each time step. Only two views have been considered for interactions in this study. Two of any agents meet randomly during the simulation and with a fixed probability rate one agent can compel another agent to

[++]Corresponding author: Emails: parus.khuwaja@usindh.edu.pk, sandar.ali@usindh.edu.pk

*Institute of Information and Communication Technology, University of Sindh, Jamshoro.

**Department of Computer Science and Software Engineering, NED University of Engineering and Technology.

follow his opinion. A small probability factor was added so that the agent can change his view at any time step independently. The behavior which was observed with the said simulation was that the interactions between agents can result in constantly varying views.

(Lux, 1998; Lux and Marchesi, 1999) divided the agents into three categories, i.e., fundamental trader, optimistic technical trader and pessimistic technical trader. The transitional probability of an optimistic technical trader to pessimistic and vice versa depends on the current value trend and opinions from the majority of technical traders. For instance, if the current value is going down and most of the technical traders are pessimistic then there is a high probability of transition from optimistic trader to be a pessimistic one. The transitional probability of a technical trader to fundamental trader depends on the rules of profitability.(Westerhoff, 2010) model recombines some of the influential concepts from the above three approaches and comes up with a trading behavior in the BMM. Similar to the previous approaches, this model also takes into account the interactions between the agents and defines a fitness function to avoid asymmetric profits. The rules are defined on the basis of weighted average profits from current and past iterations.

(Šperka and Spišák, 2013) extended the Westerhoff model by introducing the transaction cost in the fitness function. Transaction cost is mostly viewed as a negative phenomenon by many researchers but this work considers the transaction cost in a positive manner that includes, the cost of obtaining information, interpreting information, decision time, different kinds of fees, taxes and so forth, to measure the stability of the BMM.

(Schmitt and Westerhoff, 2017) extends their own model to measure the speculators herding behavior when an uncertain condition occurs. Their aim is to show that as the speculator's behavior becomes less heterogeneous the excess demand is less balanced and the value can be adjusted strongly

.

(Samanidou, Zschischang, Stauffer, and Lux, 2007) carries out an extensive review of the BMMs implemented in the previous years. The aim of their study is to monitor the scaling laws in conjunction to the BMM dynamics and to show the similarity of scaling laws with interacting subunits.

(Schmitt and Westerhoff, 2016) revisited their model and proposed a method to convert a very large-scale agent-based model to a small-scale one and proved that while scaling down the dynamics, the model is still able to produce crashes, bubbles, uncorrelated returns, fat-tailed return distributions, and clustering.

This work revisits and extends the work of Westerhoff by introducing exchange volatility variable which is affected by the security conditions of the environment. Some more rules have been derived from these variables to monitor:

- The normal behavior of model with low exchange volatility rate.
- The influence of exchange volatility rate on the stability of the BMM.
- The influence of exchange volatility rate on switching behaviors of brokers.

This paper is further structured as follows: Section 2 highlights the importance of agent-based modeling (ABM) and simulation methods for analyzing the behavior of real BMMs. Section 3 presents the Wester Hoff multi-agent BMM. In section 4 the extended model and rules derived from the original model with respect to exchange volatility rate are explained. Section 5 will present the results of the model using agent-based simulation. Implications of the current study, conclusion and future work are discussed in section 6.

2. SIMULATION OF BMM USING ABM

Efficient market hypothesis (EMH) argues that all the information regarding fair value of traded assets can be retrieved from market value but the behavior of BMMsignificantly deviates from this argument (Allen and Gale, 2003), in fact, fair value of assets and boursevalue often reflect the differences in a situation referred to as bubbles. In this situation, either the bourse is collapsed due to an oversupply of the assets or the assets are artificially overvalued due to excessive demand (James and Smith, 2000; Stein, 1995). (Shleifer, 2000) presented three basic assumptions for EMH. First, coherent agents eliminate the influence of preposterous investors on the assets. Second, the purchases will be random if some of the investors are not coherent and consequently, they both cancel out each other. Third, the assets are rated by the investors with unrestrained prudence.

ABM nowadays is gaining popularity in the applications related to sciences, such as management theory, investment, and finance fields. The representation of a company model in terms of agent-based simulation was introduced by (Vymetal and Sperka, 2011). The simulation of multi-agent model comprises of decision-makers (agents) and the interactions among them (rules) (Rutkauskas and Ramanauskas, 2009; Shleifer, 2000). The simulation environment can represent banks and governments as institutions, and BMM participants, such as brokers, supervisors, and investors as agents. In contrast to other models, the ABM does not presume that the economy should always converge to the equilibrium state, rather it models the behavior based on rules (that the agent should perform at any given time step) and the situation of the current environment. Agents take decisions for investment based on the interactions, change in environment, for instance, inflation rate, past experiences, and future expectations, respectively. The behavior of these agents is stored and simulated in a software environment to analyze its effect over a protracted period of time. Agent-based simulation and modeling have the capability to design non-linear behavior when compared to the equilibrium state. This gives flexibility to the monetarist supervisors to simulate the model behavior with varying parameters for quantitative measurements before applying or revising policies. The theory of rational expectations also gained importance in late twentieth century, also termed as behavioral economics. It implies that the supervisors can adopt promptly and coherently to new situations for maximizing their profits because of the access to the information they need. The problem with these rational expectations is that the investors do not have the ease of access to such kind of perfect information.

We use ABMs for the case of BMM as it is relatively a balanced bourse with bubbles and busts (i.e., demand roughly overlaps with the supply). In contrast to EMH, our assumptions for this model are based on (Lettau, 1997; Yang, 1999):

- The decision of agents can be influenced by the opinion of other agents.
- The decision of agents is affected by strong random factors, for instance, agent reacts to the bourse development with varying sensitivity, hence making the agents heterogeneous.
- The agents do not always interpret the situation correctly or they do not possess all the information.

3. WESTERHOFF MULTI-AGENT MODEL

The original mathematical model for the BMM was developed by Frank Westerhoff(Westerhoff, 2010). The said agent-based simulation has software agents which are distinguished as *Technical brokers* and *Fundamental brokers*. The technical broker is the one which follow the value trends and performs technical analysis to generate their opinion. On the other hand, a fundamental broker buys asset when their value is underestimated as they believe that in long term the fundamental value approximates their asset value. The change in values are reflected from a number of orders placed by fundamental and technical brokers in each iteration, this phenomenon is termed as demand excess. These agents interact and confer their performances and change their order placement rate with respect to time. The agents can be persuaded to change their trading method if the alternate broker rules are more successful. The interaction among agents is direct but random. The performance of rules is based on the past and present profit. The assumption which is taken into consideration is that the agents have the capability to determine the asset's fundamental value. The relationship between buying and selling of assets and the value change caused by this relationship is modeled using log-linear value impact function given in **(Eq. 1)**

$$P_i = P_{i-1} + P_a(W_i^T O_i^T + W_i^F O_i^F) + \alpha_i \qquad (1)$$

P_{i-1} represents the value in previous iteration where P_a refers to the positive value adjustment coefficients. W^F and W^T refer to the weights of agents using fundamental and technical rules, it also imitates the ratio between fundamental and technical agents. $O^F$and $O^T$are the orders generated by fundamental and technical brokers. α in eq. (1) is the independent and identical normally distributed random variable to bring some randomness in log-linear value function. The mean and standard deviation α is zero and σ^α. As it is already mentioned that technical broker buys the assets from the value trend analysis therefore, the formation of technical rules can be represented in **(Eq. 2)**

$$O_i^T = P_b(P_{i-1} - P_{i-2}) + \beta_i \qquad (2)$$

The deviation between the values indicate the trend and parameter $P_b$which refers to the agent sensitivity to change in value. P_b is always positive and β is the independent and identical normally distributed random variable having mean zero and standard deviation of σ^β. Fundamental broker buys the assets when their price is below fundamental value. Fundamental analysis permits the difference of fundamental value for short term and uses this analysis as approximation for the long run. The formulation for the fundamental orders is given in **(Eq.3).**

$$O_i^F = P_c(F_i - P_i) + \gamma_i \qquad (3)$$

The F_i represents the fundamental value at any given time step. For the sake of making implementation simple the value of F_i was set to be 0 in Westerhoff model. P_c is the positive term and reflects the agent sensitivity where as γ is the independent and identical normally distributed random variable having mean and standard deviation zero and σ^γ, respectively.
The weight of technical broker is given as the ratio of the total number of agents (K) to the number of technical brokers (N_x) and is
given in **(Eq. 4)**

$$W_i^T = \frac{N_x}{K} \qquad (4)$$

Similarly, the weight of fundamental broker is the ratio of the difference between thetotal number of agents and the number of technical brokers to the total number of agents, the mathematical expression is shown in **(Eq. 5)**

$$W_i^F = \frac{(K-N_x)}{K} \quad (5)$$

Both types of brokers interact with each other at every time step and discuss their success. If the rules concerning to one agent is more successful than the other, the agent can change its behavior with some probability *N*. The transitional probability of one agent changing its behavior to another is given by $(1 - \delta)$. There is also a small probability that allows an agent to change his behavior independent of the interactions, the probability is denoted as ε and *wp* refers to "with probability". The formulation of transitional probability is given in **(Eq. 6)**

$$N_x = (N_{x-1}+1)wpp_{i-2}^{+} = \frac{K-N_{x-1}}{K}\left(\varepsilon + (1-\sigma)_{x-1}^{F\to T}\frac{N_{x-1}}{K-1}\right),$$
$$N_x = (N_{x-1}-1)wpp_{i-2}^{-} = \frac{N_{x-1}}{K}\left(\varepsilon + (1-\sigma)_{x-1}^{T\to F}\frac{K-N_{x-1}}{K-1}\right),$$
$$N_x = N_{x-1}wp\ 1 - p_{i-2}^{+} - p_{i-2}^{-}, \quad (6)$$

Where the probability of a technical broker transiting to the fundamental broker is:

$$(1-\delta_{x-1}^{T\to F}) = \begin{cases} 0.5-\lambda, & for A_x^T > A_x^F, \\ 0.5+\lambda, & otherwise \end{cases} \quad (7)$$

and the probability of a fundamental broker transiting to the technical broker is:

$$(1-\delta_{x-1}^{F\to T}) = \begin{cases} 0.5+\lambda, & for A_x^T > A_x^F, \\ 0.5-\lambda, & otherwise \end{cases} \quad (8)$$

A_x^T and A_x^F, refer to the fitness rules (profitability from the past rules) for technical and fundamental brokers, respectively. The formulation of fitness rules for fundamental broker is given in (**Eq. 9).** whereas the rules for technical broker is shown in (**Eq. 10).**

$$A_x^F = (\exp[P_{i-1}] - \exp[P_{i-2}])O_{i-1}^F + dA_{x-1}^F (9)$$
$$A_x^T = (\exp[P_{i-1}] - \exp[P_{i-2}])O_{i-1}^T + dA_{x-1}^T (10)$$

The price is started from the period *t-2* and the orders are submitted in period *t-1.* Agents take into account the most recent fitness rules and calculate the profits accordingly. Variable *d* refers to the agent's memory. The value of *d* varies between 0 and 1, 0 represents memoryless agents whereas 1 represents the agents having a track of all the previous rules.

4. PROPOSEDEXTENDED MODEL

The aim of this study is to investigate the influence of security conditions and exchange rate volatility on stability as well as on the transitional behavior of the brokers. The more exchange rate volatility the less stable bourse will be. The entrance of volatility index (VI) e.g. exchange volatility will have a direct impact on the value of the asset. VI has been adopted into the formula as shown in **(Eq. 11)**

$$P_i = P_{i-1} + P_a\left(W_i^T O_i^T + W_i^F O_i^F\right) + TC - VI + \alpha_i (11)$$

In a study conducted by (Šperka and Spišák, 2013) the transaction cost (TC) was used to see the influence of stability therefore, the term is also added in the value model. In our study, we have only used VI in a negative aspect i.e., exchange rate volatility will always effect the value model in a negative way. As our aim is to develop a model that can imitate the BMM dynamics while showing the influence of VI on the value of an asset, we have only used its negative aspect. Another agent has been introduced in our model i.e., "Idle broker". As the term reflects, this trader will freeze all its trading and wait for the conditions to be better. This kind of behavior is only triggered when the security conditions become bad or worse or the conditions are being better after getting bad or worse. This phenomenon is also referred to as "trading halt". It is not always necessary that all the agents adopt the trading halt condition, in our model this transition occurs based on a certain probability. The model in (**Eq.11)** then changes to the one in (**Eq.12)** where W_i^H refers to weights for idle broker. O_i^H reflects to the orders for idle broker but as there will be none, therefore this value is constant "1" if the exchange volatility rate is greater than the threshold (*Th*) and "0" otherwise (*oth*)

$$P_i = \begin{cases} P_{i-1} + P_a\left(W_i^T O_i^T + W_i^F O_i^F + W_i^H O_i^H\right) + TC - VI + \alpha_i, VI > Th \\ P_{i-1} + P_a\left(W_i^T O_i^T + W_i^F O_i^F\right) + TC + \alpha_i, \quad oth \end{cases}. (12)$$

As one more agent has been added in our model, therefore, the probability rules have also been modified and revisited from the existing approach. Now the number of technical brokers are denoted by N_{Te}, the number of fundamental brokers are denoted by N_{Fu} and number of idle brokers are given by N_{Id}. The transitional probability formulation used in our approach is shown in **(Eq. 13)**.

$$N_x = \begin{cases} (N_{Te-1}+1), (N_{Fu-1}-1), wpp_{Te-1} = \frac{K-N_{Te-1}}{K}\left(\varepsilon + (1-\sigma)_{Te-1}^{Fu\to Te}\frac{N_{Te-1}}{K-1}\right), \\ (N_{Fu-1}+1), (N_{Te-1}-1)wpp_{Fu-1} = \frac{N_{Te-1}}{K}\left(\varepsilon + (1-\sigma)_{Fu-1}^{Te\to Fu}\frac{K-N_{Te-1}}{K-1}\right), \quad VI < Th, \\ N_{x-1}, wp\ 1 - p_{Te-1} - p_{Fu-1}, \end{cases}$$
$$N_x = \begin{cases} (N_{Te-1}+1), (N_{Fu-1}-1) \vee (N_{Id-1}-1), wpp_{Te-1} = \left(\frac{N_{Fu-1}}{K}\right)\left(\frac{N_{Id-1}}{K}\right)\left(\varepsilon + (1-\sigma)_{Te-1}^{Fu,Id\to Te}\frac{N_{Te-1}}{K-1}\right), \\ (N_{Fu-1}+1), (N_{Te-1}-1) \vee (N_{Id-1}-1), wpp_{Fu-1} = \left(\frac{N_{Te-1}}{K}\right)\left(\frac{N_{Id-1}}{K}\right)\left(\varepsilon + (1-\sigma)_{Fu-1}^{Te,Id\to Fu}\frac{N_{Fu-1}}{K-1}\right), \\ (N_{Id-1}+3), (N_{Fu-1}-3) \vee (N_{Te-1}-3), wpp_{Id-1} = \left(\frac{N_{Te-1}}{K}\right)\left(\frac{N_{Fu-1}}{K}\right)\left(\varepsilon + (1-\sigma)_{Id-1}^{Te,Fu\to Id}\frac{N_{Id-1}}{K-1}\right), \\ N_{x-1}, wp\ 1 - p_{Te-1} - p_{Fu-1} - p_{Id-1}, \end{cases} VI > Th \quad (13)$$

The formulation of fitness rules will remain same as the idle trader as it is only based on the trigger from volatility index if it goes beyond a certain threshold. The reason for adding more idle brokers in comparison to the technical and fundamental brokers is that the technical broker only considers the value trend which is not stable when the volatility index goes beyond a certain threshold level and fundamental broker take into account all the previous values for trading. Hence, there should be relatively lower probability that an agent tries to transit its behavior towards technical or fundamental trading than going into a trade halt state. The threshold for the VI is set to be 0.03, this threshold was selected to visualize the effects on a frequent basis. The rules for computing volatility index through security conditions are kept simple and derived using simple statistical equation shown in(**Eq. 14)**

$$VI_i = \begin{cases} VI_{i-1} - \eta C, & if SC \leq 0.5 \\ VI_{i-1} + \eta C, & if SC > 0.5 \end{cases} \quad (14)$$

SC in the above equation is referred to as the security condition, C refers to a constant value and η refers to the varying rate, suggesting that the volatility rate can be decreased or increased with speeding rate with respect to the changing security conditions.

5. RESULTS AND DISCUSSION

In this section, we present the model simulation results using the ABM. The model implementation was done in Net Logo platform. Net Logo was initially developed by Uri Wilensky (Wilensky and Evanston, 1999), it is a software platform for modelling natural sciences problem. The usage of this software was started in 1999 while the development is still in progress and is widely used for simulation modelling purpose. This tool is a variant of original Logo language and has programming capabilities that can support ABM. It also provides a visual interface to analyze the simulation effect instantly. The model developed in NetLogo is shown in (**Fig.1)**. The extreme left side of the interface shows the initialize and simulation button along with all the input parameters provided by the user. The main visualization window shows the simulation at each time step. Extreme right shows the plotting results for the current value, returns, weight rules for fundamental and technical brokers and transitional probabilities for fundamental, technical and their combined probabilities. Extreme bottom values show the calculations measured from the simulation for different variables.Our simulation results are measured for 3 cases. Case 1 refers to the normal case having good security conditions throughout. Case 2 refers to the security conditions varying throughout the simulation but ultimately gets better till the end. Case 3 refers to the security conditions that starts being bad from the middle of the simulation and gets worse until the end. The simulation parameters used for the simulation is shown in (**Table 1).**

5.1 Case 1:

Case 1 is the normal case having ideal security conditions and as the exchange volatility rate is only affected by the security conditions in our model, therefore, the model will run same as the Westerhoff model. It validates that the presented model can imitate the normal behavior of the BMM as well. (**Table2**).show the results for the environment having a low, medium and high number of agents with a varying number of iterations. The maximum iteration is set to be 10000 (days) and the step to record the results is set to be 1000.

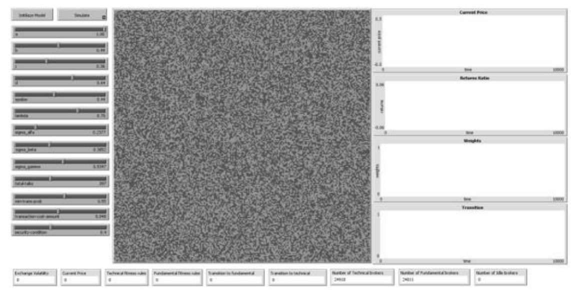

Fig.1. Agent-based simulation for BMM

Table 1 Simulation parameters for BMM

Parameter	Value
a	1.00
b	0.49
c	0.36
d	0.64
Epsilon (δ)	0.44
Lambda (λ)	0.70
Sigma alfa (σ^{α})	0.2377
Sigma beta (σ^{β})	0.3852
Sigma gamma (σ^{γ})	0.5347
Total talks(number of interactions)	397
Min-trans-prob (Minimum transition probability)	0.55
Transaction-cost-amount (TC)	0.048
Security-condition (SC)	(0.0 – 1.0) good to worse

In the normal situation, the fundamental brokers transit their behavior more towards the technical brokers and same is the case shown in the result of case 1. All the results presented in (**Table 2**) are averaged results from 10 rounds of simulation. It is also analyzed that the probability distribution of fundamental broker varies much more as compared to the technical broker which has quite a normal trend for the transitions. The result of probability distributions for both agents is shown in (**Fig.2).**

5.2 Case 2:

In case 2 the security condition is varied from time to time in the model. As it has been analyzed from (**Table 2**). that a number of agents has not a vital role to play in our cases, therefore, we will limit our variations of the number of agents to 2500 and 50000, respectively. In (**Table 3).** the number of idle brokers isalso added and the transitional probability of both the agent's i.e., fundamental and technical brokers is shown in (**Fig. 3)**

Table 2 Case 1 average results

# Iter	V.P	# of TB	# of FB
	# of Agents (5000)		
0	0	2467	2634
1000	1.0753	4613	488
2000	-0.1531	3640	1461
3000	-1.8088	3460	1641
4000	0.0688	3696	1405
5000	0.3796	3426	1675
6000	-0.6213	3445	1656
7000	1.8695	3837	1264
8000	0.4237	3447	1654
9000	0.2002	4081	1020
	# of Agents (25000)		
0	0	12637	12644
1000	0.0057	18505	6776
2000	-0.3282	18261	7020
3000	-0.9592	18334	6947
4000	-0.1624	18498	6783
5000	0.3404	18160	7121
6000	-0.0905	18297	6984
7000	1.3732	18319	6962
8000	0.2636	18317	6964
9000	1.0469	18150	7131
	# of Agents (50000)		
0	0	24997	24732
1000	0.3913	35942	13787
2000	1.8646	36173	13556
3000	-0.4775	36193	13536
4000	1.1066	35992	13737
5000	-0.3169	36410	13319
6000	0.2279	35961	13768
7000	-0.2125	35923	13806
8000	-0.1372	35992	13737
9000	0.0265	35941	13788

Iter: Iterations, V.P: Value Price, # of TB: number of technical brokers, # of FB: number of fundamental brokers

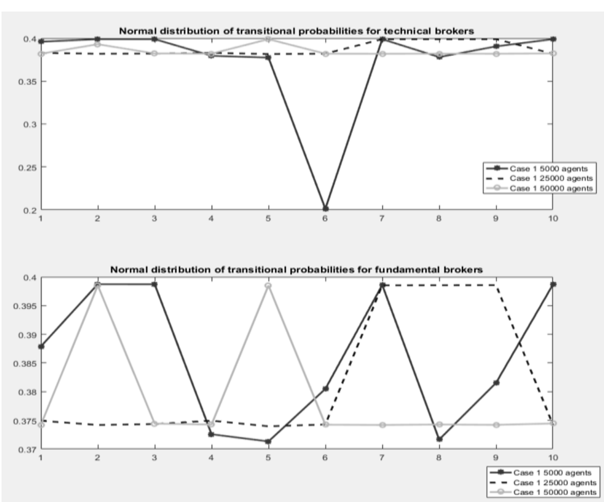

Fig.2. Transitions for case 1

It proves that by adding exchange volatility rate can cause abrupt transitions between the agents, previously in (**Fig. 2**) the transitional changes for technical brokers were not so frequent but it can be visualized that by varying the exchange volatility rate the probability distribution is random as it was the case with fundamental brokers.

Table 3 Case 2 average results

# Iter	V.P	# of TB	# of FB	# of IB
	# of Agents (5000)			
0	0	2463	2638	0
1000	0.2755	3654	1447	0
2000	-0.8063	3830	1271	0
3000	0.8304	2351	2070	680
4000	-0.4817	2275	1872	954
5000	-0.2142	3689	1404	8
6000	-0.6802	3184	1687	230
7000	-0.3162	2230	1850	1021
8000	0.5874	2417	1648	1036
9000	-0.0666	3650	1283	168
	# of Agents (50000)			
0	0	24808	24921	0
1000	0.9275	35892	13837	0
2000	-0.6881	22286	18277	9166
3000	-0.0668	23287	18191	8251
4000	0.1323	29903	14011	5815
5000	-0.2980	35942	11645	2142
6000	0.5480	36142	11596	1991
7000	-0.2155	25204	20171	4354
8000	0.5651	25011	19670	5048
9000	0.5472	33364	13680	2685

Iter: Iterations, V.P: Value Price, TB: Technical broker, FB: Fundamental broker, IB: Idle broker

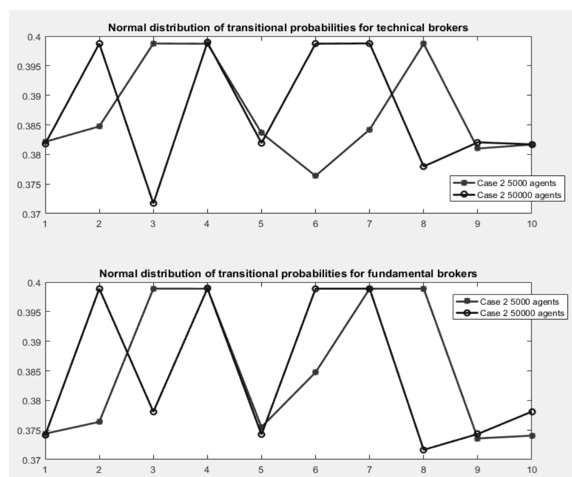

Fig. 3.Transitions in Case 2

Also, it is analyzed that exchange volatility rate can cause the price change to vary randomly, though when the exchange rate volatility starts to add up the current price initially goes down but as the volatility rate continues to add the cost price randomly increases or decreases. Our second aim which was to prove that volatility rate effects the current price is reflected in the results presented in (**Table 3).**

5.3 Case 3

In Case 3, the security conditions will start getting bad from the middle of the simulation but it will get worse until the end of the simulation. (**Table 4**). presents the result from the case 3 where the environment and the number of agents will be varied similarly to case 2. Case 3 analyzes the long-term effect of the volatile situation. It can be noticed from (**Table 4).**

Table 4 Case 3 average results

# Iter	V.P	# of TB	# of FB	# of IB
	# of Agents (5000)			
0	0	2463	2638	0
1000	-0.4131	3700	1401	0
2000	0.2776	3620	1481	0
3000	-0.2882	4058	1043	0
4000	0.5341	3688	1413	0
5000	0.1844	3622	1479	0
6000	-0.1739	2825	1844	432
7000	-0.2108	2937	1875	289
8000	0.5124	2749	1854	498
9000	0.6092	2650	1844	607
	# of Agents (50000)			
0	0	24808	24921	0
1000	-0.4111	35677	14052	0
2000	-0.4691	36011	13718	0
3000	0.1031	36016	13703	0
4000	0.5869	36030	13699	0
5000	0.1036	36159	13570	0
6000	-0.1907	27288	20225	2216
7000	0.1318	34711	11466	3552
8000	-0.1681	25118	20216	4395
9000	0.1304	24052	21252	4425

Iter: Iterations, V.P: Current Price, TB: Technical broker, FB: Fundamental broker, IB: Idle broker

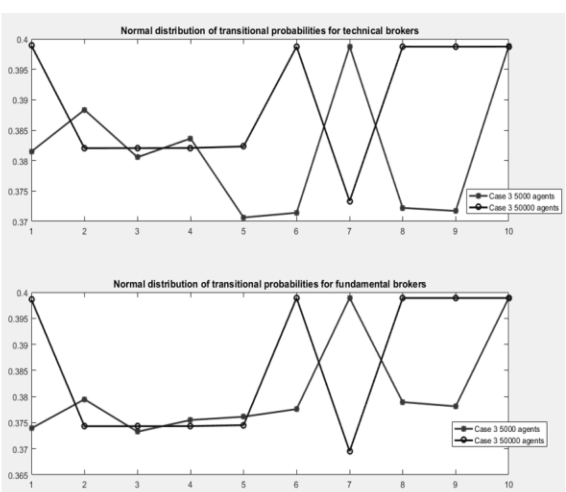

Fig.1 Transitions for Case 3

(**Fig. 4**). show the transitional probability trend for fundamental and technical broker and it is determined from the plots that if the volatile situation continues for the long run then the probability trend of fundamental and technical broker yields similar graph.

7. CONCLUSION

The main focus of this paper is to introduce the ABM for the simulation of problems related to natural sciences which cannot be applied with conventional approach in real-world settings. The modeling allows us to simulate the behavior patterns of certain phenomenon where acquiring data is not practically possible. The knowledge-driven approach of agent based modeling provide us insights for the behavior analysis and noticeable parameters which could affect the simulation and its working with permissible certainty. Although, the knowledge-driven rules should be carefully chosen so that the authenticity of the simulation can be entrusted. In this paper, we have extended Westerhoff BMM in terms of the volatility rate and an addition of an agent i.e. idle broker. We have presented the formulations through which we implement the extension to the trading phenomenon. The model is developed using agent-based simulations and is capable of imitating the BMM dynamics. As it is shown in the results that if the security conditions are stable the BMM imitates the normal behavior of market dynamics as it was proposed by Westerhoff. The volatility rate is triggered by the security conditions if they start getting bad or worse.

The volatility rate not only affects the current value but also affects the transition behavior of the broker's i.e., technical and fundamental broker. Three cases have been proposed and the trend has been plotted accordingly. It is shown that if the exchange rate fluctuates continuously throughout the simulation, the trend for transition behaviors of brokers and the current price tends to be random but if the volatile situation continues for a long time then the model has the tendency to stabilize itself, as the fundamental trading rules overbear the technical trading rules. Although the crashes and bubbles occur they will not impact the behavior significantly as the asset target the fundamental value gradually. The model can depict some real-life scenarios of the trade bourse in the middle east where the security condition is not stable.

By adding the exchange volatility rate to the log-linear value model we can observe the current value change. When the volatility-index in the model fluctuates continuously between stable and notstable the value goes up or down abruptly which creates bubbles and crashes. But at times the volatility can help in eliminating those bubbles. In the simple model, the transaction cost makes the value grow and the technical brokers overtake the BMM which also creates bubbles. Introducing the volatility-index in the model can eliminate those bubbles as the technical broker's transit to fundamental and idle brokers abruptly. This is one of the main contributions of this paper in conjunction with the transitional behavior of the agents. In the simple model if transaction cost goes down (Šperka and Spišák, 2013) the value disproportionately goes high without limit, thus the bourse dynamics are destabilized, in this case, the volatility-index can also play a vital role for compelling the bourse dynamics to be stabilized.

This paper demonstrates the positive impacts of volatility-index introduced in the BMM and the log-linear value model. The future directives for this research are to optimize the values for transaction cost, volatility-index, and transitional probabilities to construct a BMM with stability for a long run. More rules can be developed and the model can be simulated by using the secondary data provided by the real-life.

It can also be noted that this paper proves the applicability of the ABM and simulation for behavior analysis of phenomenon which are hard to imitate with data-driven approaches. This knowledge-driven approach can be applied to enormous applications such as behavior of truck drivers in day-time and night-time driving, evaluating administrative policies by simulating office-work spaces, and so forth. This will not only allow us to observe the behavior of agents in the created environment but also provide us insights with the probable directions and significant parameters to control for desired outcomes.

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