An Artificial Market Analysis of Exchange Rate Dynamics

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Abstract

In this study, we propose an exchange market model with artificial adaptive agents (AGEDASI TOF) and conduct a computer simulation as a study on the *artificial market*. First, AGEDASI TOF is compared with a random walk model and a linear regression model in out-of-sample forecasts. The results indicate that AGEDASI TOF outperforms the other models over all forecast horizons. Next, we analyze an exchange rate bubble in the real world using AGEDASI TOF. From the results, we conclude that the bubble starts by support of fundamental factors, grows by bandwagon expectations, stops by coincidence of all agents' expectations, and collapses by regressive expectations. This study shows that the artificial market approach is effective not only for qualitative analysis but also for quantitative analysis of economic systems in the real world.

1 Introduction

Psychological or behavioral aspects in economic phenomena has been recognized as important, since the recent economic bubbles and their collapses. For example, one of the important causes of the exchange rate bubbles is said to be bandwagon expectations[1] [5]. Such phenomenon shows that agents make predictions not independently but instead by interacting with each other.

However, conventional economic theories of an exchange market usually ignore such behavioral features by assuming a Rational Expectations Hypothesis (REH). REH assumes that expectations of all agents are essentially the same. By this strong assumption, REH does not describe agents' adaptive behavior. However, in recent years, this avoidance has been pointed out to be problematic. Moreover, recent empirical tests have revealed that REH models do not follow actual phenomena.

Several alternative approaches has been proposed. Among these, there are *artificial market* approaches [1, 2, 4, 6, 9, 10]. Studies based on these approaches develop market models with artificial adaptive agents and conduct computer simulations. In these studies, they analyze the evolution of models to understand markets in the real world *qualitatively*.

But, in the artificial market approaches, no studies have ever tried to analyze the real markets *quantitatively*. This is because conventional models have a problem: they don't deal with agents' mental models of economic structures. This study is considered to be the first attempt to apply the artificial market approach to *quantitative* analyses of the real markets.

In this paper, admitting the artificial market approach, we propose a new model of a foreign exchange market using genetic algorithms (GA) which is named **A GE**netic-algorithmic **D**ouble **A**uction market **SI**mulation in **TO**kyo **F**oreign exchange market (AGEDASI TOF[2]).

In this study, we evaluate the model in two ways: First, we compare AGEDASI TOF in out-of-sample forecasts with two conventional models: a random walk model and a linear regression model. Second, we apply AGEDASI TOF to quantitative analyses of an exchange rate bubble in the real world.

This paper is organized as follows: In Section 2, we explain conventional models of foreign exchange markets and their problems. And, in order to propose the new model, we describe main features of exchange markets in the real world and their similarities to biological genetics. In Section 3, we explain the proposed model, AGEDASI TOF. In Section 4, we conduct two simulations using AGEDASI TOF: out-of-sample forecasts comparison and analysis of an exchange rate bubble. In section 5, this paper is concluded.

[1] The word "bandwagon" means that many people join others in doing something fashionable or likely to be successful. That is, many agents (or participants) in a market ride along with the recent trend.

[2] AGEDASI TOF is a name of a Japanese dish, fried tofu, which is very delicious.

2 Preliminary

2.1 General Framework of Previous Studies

Usually conventional economic models of foreign exchange markets include the following four steps explicitly or implicitly (Fig. 1).

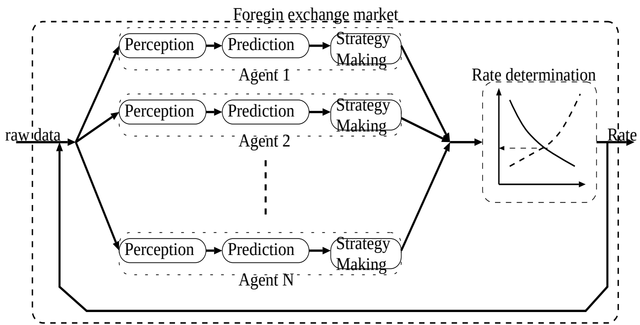

Figure 1: General framework

First, each agent expects future exchange rates from some related information. Then, using this expectation, he actually submits bids and/or asks to the market. It is assumed that this decision-making process is divided into three steps:

Perception: Each agent interprets changes of various raw data such as economic indicators and political news, and perceives factors of rate prediction. In this step, each agent interprets the data independently and does not consider relations to the other data and to the rates yet.

Prediction: By using their own percepted factors, each agent predicts future economical situations and future changes of exchange rates.

Strategy Making: With his own predicted rates, each agent decides the order rates and the order quantity to buy or sell currencies.

As a consequence of this series of decision-making, each agent submits a bid or an ask. By aggregating whole bids and asks in the market, we can draw the supply and demand curve.

Rate Determination: The exchange rates are decided to the equilibrium rates where supply and demand meet.

2.2 Problems of REH

Rational expectations hypothesis (REH), a prevailing hypothesis used in economic theories, makes the following strong assumptions on the above general framework:

Assumption 1: All agents are the same in the Decision Making Process: Perception step, Prediction step, and Strategy Making step. That is, all agents have complete information and the same mental model, and select an optimal behavior which maximizes the same utility.

Assumption 2: All agents know that all agents are the same in the above three steps. Moreover, all agents know that all agents know it.

Based on these assumptions, expectations of all agents are fundamentally[3] the same. Therefore, REH avoids describing agents' adaptive behavior.

However, recently, REH has been pointed to have the following problems:

1. The real markets rarely satisfies all the above assumptions, because it has complex and nonlinear interaction among agents.

2. REH cannot explain adaptive behaviors of agents, though these behaviors are very important in the real world. In the real world, each agent always improves his own mental model. Such adaptive behaviors will decide the real exchange rates.

3. Recent empirical tests[4] have revealed that REH models do not explain rate dynamics in the real world.

Because REH has these theoretical and empirical problems, it is recently said that economic models which are not based on REH are needed. These models must apply concrete learning algorithm to the description of adaptation behavior of agents.

In the next subsection, in order to find the learning algorithm which is suitable for the description of the agents' adaptation, we observe main features of the real markets through both books and interviews with dealers. And we propose a new hypotheses from the viewpoint of similarities between the real markets and biological genetics.

2.3 Similarities between a Market and Genetics

In an exchange market in the real world, each agent builds up his own belief system, which consists of beliefs about factors[5], and improves his own belief system by

[3]If any differences exist, they are caused by only random factors [8].

[4]The cointegration tests, survey data tests, out-of-sample forecasts tests, and so on.

[5]Factors are related information which are thought to cause to change the rate. For example, interest rates, VIP announcement, balance of trade, stock price, political news,and so on. Beliefs about factors are agents' beliefs about what factors are important for forecasts of future rate changes. In other words, they are agents' mental models of the exchange market.

communicating with other agents. However, REH models are built up from the agent level; their components are fixed rational agents. If REH models have the problems, why not build up a model from a lower level such as the belief level? We consider beliefs about factors as components of our model.

Through books and our interviews with dealers, we find that beliefs about factors have the following important features:

1. They are *replicators*: they are imitated or transmitted by other agents with some degree of reproductive accuracy.

2. They are *instructors*: they organize each agent's belief system about the market, and according to his own belief system, each agent makes the prediction and decides his behaviors.

3. They are under *selective pressure*: each agent always replaces his old beliefs with new more successful ones, in order to improve his predictions[6]

4. They have *sustained variation*: each agent generates a new belief system by communicating with other agents[7] or by himself.

Judging from the viewpoint of these features, beliefs about factors are seen to be similar to biological genes (Fig. 2). As are discussed above, we will state the

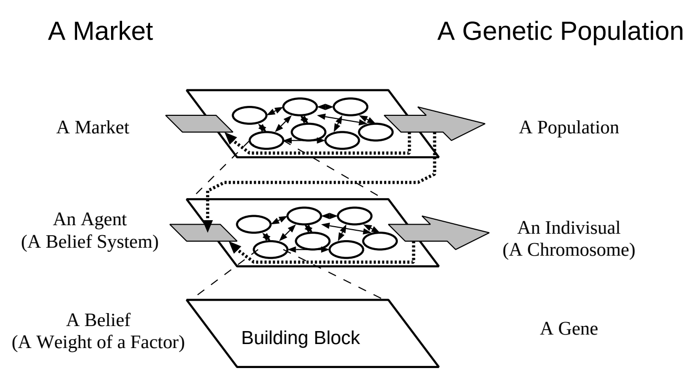

Figure 2: Analogy between a market and genetics: the systems at the lower levels are the components of the systems at the upper levels.

following hypothesis. Each agent behaves based on his own belief system and the behavior of agents changes the environment,that is, the exchange rates. The belief system of each agent changes in time, influenced by other agents' belief system. This procedure is similar to adaptation in the ecosystem. In this study, the adaptation in the market is described with GA, which based on ideas of population genetics.

3 Construction of AGEDASI TOF

AGEDASI TOF adds the *adaptation* step to the former four steps in the general framework (Fig. 1). Using weekly data in Tokyo foreign exchange market, AGEDASI TOF iteratively executes the following five steps:

1. **Perception**: interpretation of raw data.

2. **Prediction**: prediction of the future rate.

3. **Strategy Making**: submission of order.

4. **Rate Determination**: determination of the equilibrium rate.

5. **Adaptation**: change of prediction methods.

These five steps forms a *generation* in GA terms. Each generation starts at the perception step and ends at the adaptation step.

3.1 Perception

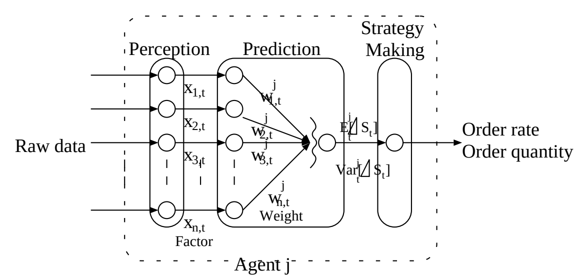

Figure 3: the decision-making process: the Perception, Prediction, and Strategy Making step.

First, each agent interprets raw data and perceives factors affecting the rate change. $x_{i,t}$ is defined as a factor which is made by interpreting raw data i between the end of generation $t-1$ and the beginning of generation t. In our present study, it is assumed that all agents interpret raw data in the same way. Thus the same $x_{i,t}$'s are substituted into the prediction step of each agent.

Data series of factors are made by coding degrees of 17 data (Shown in Table 1). A *Fundamentals factor* is defined as a factor made from the data on economic fundamentals or political news in the real world (No. 1 - 14). A *trend factor* is defined as a factor made from the

[6] Many books and our interviews with dealers suggest that, in the real markets, most dealers believe that there is no *grand theory* of exchange rate dynamics; effects of factors on the rates are very changeable.

[7] Most dealers often exchange their beliefs with each others as suggested by both many books and our interviews with dealers.

	Factors ($x_{i,t}$)	Raw Data
1	Economic Development	[U] GDP,NAPM Index etc. [J] GNP
2	Price	[U][J] Consumer Price Index,Producer Price Index
3	Interest	[U][J] the official rate,Long Term Interest Rate
4	Money Supply	[U][J] Money supply
5	Balance	[U][J] balance of trade
6	Employment	[U] Unemployment Rate, Nonfarm Employment, Initial Claims
7	Consumption	[U] Retail Sales, Individual Income
8	Intervention	[U][J] Intervention
9	VIP Announcement	[U][J] Announcement of president, FRB chairman etc.
10	Mark	the dollar/mark, yen/mark exchange rate
11	Oil	Oil Price
12	Politics	Political Condition, International Affairs
13	Stock	[U][J] Stock Price
14	Bond	[U][J] Bond Price
15	Short-Term Trend 1	Change in the last week : ΔS_{t-1}
16	Short-Term Trend 2	Change of Short-Term Trend 1 : $\Delta S_{t-1} - \Delta S_{t-2}$
17	Long-Term Trend	Change through five weeks : $S_{t-1} - S_{t-6}$

Table 1: Factors ([U]=USA, [J]=JAPAN. S_t denotes a logarithms of the exchange rate at t.)

data on shot-term or long-term trends of the chart in the artificial market (No. 15 - 17).

The factors $x_{i,t}$ value between $+3$ and -3. Plus values indicate that the change of the data causes yen appreciation in the original economic theories and minus values yen depreciation. For instance, a comment "Unemployment Rate of the United States decreased largely" is coded as "Employment : -3". The data "Last week, the yen/dollar rate decreased beyond expectation" is coded as "Change in the last week : $+2$".

While the conventional artificial market approaches use only the trend data in the artificial market, AGEDASI TOF uses both the trend data and data about economic fundamentals and political news in the real world. This difference reflects the fact that AGEDASI TOF considers each agent's mind model of the market structure but that the conventional approaches don't consider it.

3.2 Prediction

After the perception, using the above factors, each agent predicts the future change of the rate. No conventional artificial market approaches explicitly describe the Prediction step. This is because this step is related to each agent's mind model of the market structure and the conventional approaches don't consider it.

In AGEDASI TOF, $w^j_{i,t}$ is defined as a weight of each factor i in each agent j's prediction of the future rate at generation t The value of $w^j_{i,t}$ changes among nine values $\{\pm 3, \pm 1, \pm 0.5, \pm 0.1, 0\}$.

With his own weights, each agent j predicts change of logarithms of the rates $\Delta S_t = S_t - S_{t-1}$, where S_t denotes a logarithm of the exchange rate at generation t. It is assumed that each agent j predicts ΔS_t based on the summation of products of the factors $x_{i,t}$ and the weights $w^j_{i,t}$. By substituting this summation into a truncation function f, each agent makes his prediction value $\mathbf{E}^j_t[\Delta S_t]$. This is represented as follows:

$$\mathbf{E}^j_t[\Delta S_t] \equiv f\left(\sum_{i=1}^{n} w^j_{i,t} x_{i,t}\right),$$

where n denotes for the number of the factors. It is also necessary to measure how factors distribute. A reciprocal of the variance of prediction is defined as follows:

$$\left(\mathbf{Var}^j_t[\Delta S_t]\right)^{-1} \equiv \sqrt{|(wx_+)^2 - (wx_-)^2|},$$

where wx_+ denotes the summation of $w^j_{i,t}x_{i,t} > 0$ and wx_- the summation of $w^j_{i,t}x_{i,t} < 0$. It must be noted that $\mathbf{E}^j_t[\Delta S_t]$ and $\mathbf{Var}^j_t[\Delta S_t]$ are different for both each agent j and each generation t because the weights are different.

3.3 Strategy Making

Based on his own prediction, each agent decides his order rate and his order quantity to buy or sell currencies, maximizing his utility function. In AGEDASI TOF, the utility functions of all agents are assumed to be the same. Each agent divides his whole assets between dollar assets and yen assets with the optimal ratio which maximizes his expected return of the next generation. Because each agent is assumed to have the same utility which is represented by a minus exponential function, the optimal quantity of his dollar assets q^{j*}_t is as follows:

$$q^{j*}_t = \frac{1}{a}\frac{\mathbf{E}^j_t[\Delta S_t]}{\mathbf{Var}^j_t[\Delta S_t]},$$

where $a(>0)$ denotes a risk aversion constant in economics. In order to coincide his holding quantity with the optimal quantity, each agent orders the same quantity as the difference between the optimal quantity q_t^{j*} and the previous holding quantity q_{t-1}^j:

$$\text{Order quantity } \Delta q_t^{j*} \equiv q_t^{j*} - q_{t-1}^j.$$

If $\Delta q_t^{j*} > 0$, then he orders to buy dollars, that is, submits a bid. If $\Delta q_t^{j*} < 0$, then he orders to sell dollars, that is, submits an ask. And each agent orders the same rate as the predicted rate, that is, buyers (respectively, sellers) are willing to buy (resp., sell) currencies when the rate is lower (resp., higher) than the predicted rate;

$$\text{Order rate} \equiv \mathbf{E}_t^j[\Delta S_t].$$

3.4 Rate Determination

After the submission of orders, the demand and supply determine the equilibrium rate (Fig. 4).

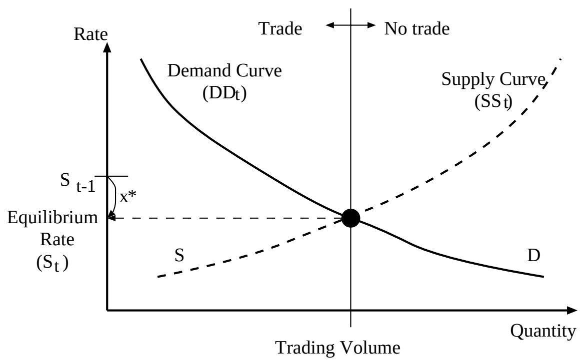

Figure 4: Rate Determination

The demand curve $\mathbf{DD}_t(x)$ is made by the aggregation of the whole bids ($\Delta q_t^{j*} < 0$) of agents having higher order rates than x:

$$\mathbf{DD}_t(x) = \textstyle\sum_{j \in J_x^D} \Delta q_t^{j*},$$
$$\left(J_x^D \equiv \{j:\ \Delta q_t^{j*} < 0 \text{ and } \mathbf{E}_t^j[\Delta S_t] \geq x\}\right).$$

The supply curve $\mathbf{SS}_t(x)$ is made by aggregation of the whole asks ($\Delta q_t^{j*} > 0$) of agents having lower order rates than x:

$$\mathbf{SS}_t(x) = \textstyle\sum_{j \in J_x^S} \Delta q_t^{j*},$$
$$\left(J_x^S \equiv \{j:\ \Delta q_t^{j*} > 0 \text{ and } \mathbf{E}_t^j[\Delta S_t] \leq x\}\right).$$

The exchange rate of the market is decided to the equilibrium rate, where quantity of demand and that of supply are equal:

$$S_t = S_{t-1} + x^*,\ (\mathbf{DD}_t(x^*) = \mathbf{SS}_t(x^*))\,.$$

Buyers (respectively, Sellers) with higher (resp., lower) order rates execute their exchanges and coincide their holding quantities q_t^j with the optimal quantities q_t^{j*}. However, the other agents do not execute their exchanges and q_t^j remains the previous holding quantity q_{t-1}^j:

$$q_t^j = \begin{cases} q_t^{j*} & \text{if } j \in J_{x^*}^S \text{ or } J_{x^*}^D \\ q_{t-1}^j & \text{otherwise} \end{cases}.$$

3.5 Adaptation

AGEDASI TOF abandons the REH's assumptions. So, the prediction methods are different among agents in AGEDASI TOF. The differences of prediction methods are represented by the differences of the weights $w_{i,t}^j$.

It is necessary to describe changes of the weights, which is a result of the adaptation of each agent. In order to describe such adaptation, as we have mentioned in 2.3, AGEDASI TOF applies GAs (Fig.5).

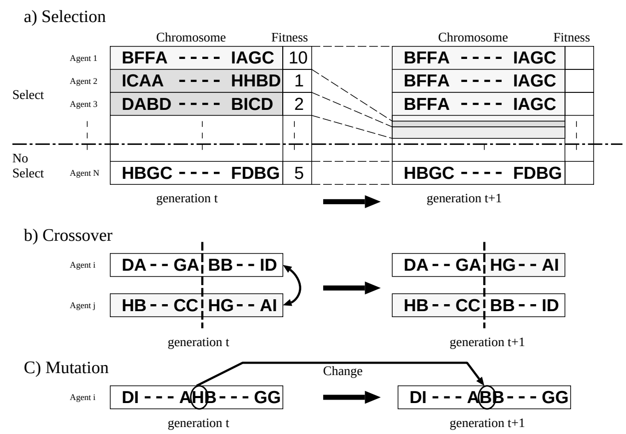

Figure 5: Genetic Algorithm in the Adaptation step: An individual is a string of all weights of one agent, that is, his prediction method. A fitness value reflects accuracy of each prediction method.

In AGEDASI TOF, a gene represents a symbol made by the transformation of a weight $w_{i,t}^j$. A weight $w_{i,t}^j$ is transformed as follows.

$$w_{i,t}^j = \begin{pmatrix} 3 & 1 & 0.5 & 0.1 & 0 & -0.1 & -0.5 & -1 & -3 \\ \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow \\ \mathbf{A} & \mathbf{B} & \mathbf{C} & \mathbf{D} & \mathbf{E} & \mathbf{F} & \mathbf{G} & \mathbf{H} & \mathbf{I} \end{pmatrix}$$

A chromosome represents a string of all weights of one agent:

$$\text{Chromosome } \mathbf{w}_t^j = (w_{1,t}^j, w_{2,t}^j, \cdots, w_{n,t}^j).$$

For example, a set of weights $\{w_{i,t}^j\} = (+0.1, -3, 0, +1, \cdots, +0.5)$ becomes a chromosome $\mathbf{DIEB}\cdots\mathbf{C}$. A population of chromosomes represents a set of $\mathbf{w}_t^j$ in the whole market. The fitness value of each chromosome is a product of -1 and an absolute value of a difference between his own predicted rate $\mathbf{E}_t^j[\Delta S_t]$ and the equilibrium rate ΔS_t:

$$\begin{aligned}\text{fitness of } \mathbf{w}_t^j &= -|\mathbf{E}_t^j[\Delta S_t] - \Delta S_t| \\ &= -|f\left(\sum_{i=1}^{n} w_{i,t}^j x_{i,t}\right) - \Delta S_t|.\end{aligned}$$

It should be noted that the more precisely a chromosome $\mathbf{w}_t^j$ predicts the rate, the higher its fitness value.

AGEDASI TOF uses GAs in a different way from usual GA applications. In AGEDASI TOF, the fitness function is not given, but is decided autonomously as the result of agents' interaction: the computation of the fitness values uses the equilibrium rate, which are determined by the whole market. In other words, AGEDASI TOF uses GAs not for optimization to the fixed best function but for description of population dynamics[8].

AGEDASI TOF is implemented based on Goldberg's simple genetic algorithm [3]. In a percentage of the population, chromosomes with higher fitness values are selected and copied at each generation, and the other chromosomes are maintained. This percentage of selection is called a *generation gap*. The crossover operator is the usual single point crossover and the mutation operator changes a value of randomly selected gene to a number uniformly distributed between -3 and +3. The crossover (respectively, mutation) operator occurs at a certain rate (*crossover rate*) (resp., *mutation rate*) [9].

GA operations can be interpreted economically as follows: Each chromosome can be regarded as each agent's belief system about the exchange market. That is, it represents which factors are regarded as the important causes of the rate change. In order to improve his prediction, each agent changes his own belief system with the three operators: selection, crossover, and mutation.

The selection operator is regarded as the imitation of successful belief systems of other agents. Therefore, belief systems with low prediction performance will disappear from the market. The other two operators are regarded as the production of new belief systems: the crossover operator works like the agent's communication with other agents[10] and the mutation operator does the independent change of each agent's belief system.

After each agent changes his belief system, generation t ends and AGEDASI TOF proceeds to the next generation $t+1$.

3.6 Dynamics of AGEDASI TOF

In our simulation, one generation corresponds to one week in the real world, because we rely on weekly data. The initial populations are randomly generated. During the first dozens of generations, it does not execute the rate determination step and uses the real world's rate data as samples. And it computes fitness values of agents using the real world's rate data, instead of the equilibrium rate in Rate Determination step. After these *sample periods*, it will not use the real world's rate data at all, and determines the equilibrium rates autonomously. And it computes fitness values using the equilibrium rate data, instead of the real world's rate data. Thus, after the sample period, AGEDASI TOF does not use the real world rate data, but uses artificial rate data, which are autonomously decided.

4 Evaluation of AGEDASI TOF

4.1 Comparison of the models out-of-sample

In order to evaluate AGEDASI TOF, we compare it with two other models, a random walk model (RW) and a linear regression model (LR), in out-of-sample forecasts. The conventional artificial market approaches cannot conduct such *quantitative* comparisons. Because of the mentioned characteristics, AGEDASI TOF can analyze the real markets *quantitatively*.

RW has a drift coefficient and use no explanatory variables. It must be noted that RW does not consider economical models of the market. LR uses the external and internal factors (Table 1) as explanatory variables. These factors include all variables used in many reduced-form equations of REH. Previous studies found that the the reduced-form equations fail to improve on RW in out-of-sample forecasting [7].

Methods To compare the models, we use weekly data series between January 1986 and December 1993 in Tokyo foreign exchange market. These data series consist of the rate data and the factor data. RW and LR are initially estimated using the data through the first sample period, between January 1986 and December 1987. Using the estimated parameters and the explanatory variables, these two models forecast the exchange rates k=1,4,13,26, and 52 weeks ahead from the end of the sample period. Then, extending the sample period 26 weeks ahead, we reestimate the coefficients of each model and generate new forecasts at the above five horizons. This procedure is conducted until the data is exhausted (Fig. 6).

In the same way, AGEDASI TOF is initially trained using the actual rate data and the factor data through the first sample period and forecasts are generated at the above five horizons. Then, extension of the sample period and new forecasts are repeated. AGEDASI TOF runs 50 times under each parameter set of crossover rate (pcross=0.9,0.6,0.3), mutation rate (pmut=0.3,0.03,0.003), and generation gap

[8] Hence, AGEDASI TOF is differ from GA's applications to search for the best fixed forecast method.

[9] The rates in the simulation will be concretely described in section 4.1.

[10] As we noted in 2.3, exchange of beliefs among dealers is very frequent in the real markets.

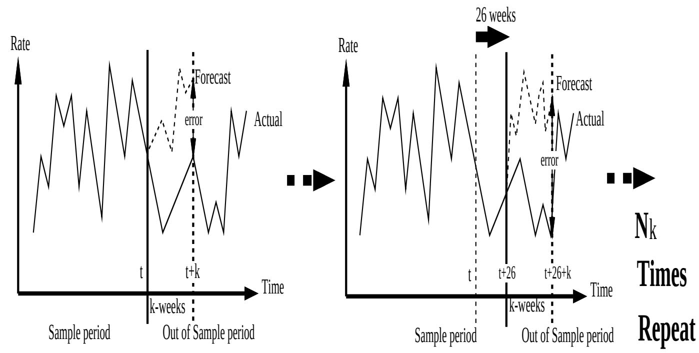

Figure 6: Out-of-sample forecast

MAE

	RW	LR		AGEDASI TOF	
k=1	0.98	1.19	(+21%)	0.86	(-12%)
k=4	1.33	3.05	(+130%)	0.94	(-29%)
k=13	6.27	7.44	(+19%)	5.43	(-13%)
k=26	8.60	10.46	(+22%)	6.48	(-25%)
k=52	10.59	11.41	(+8%)	7.33	(-31%)

RMSE

	RW	LR		AGEDASI TOF	
k=1	1.16	1.39	(+20%)	1.09	(-6%)
k=4	1.73	3.83	(+121%)	1.25	(-28%)
k=13	6.91	8.52	(+23%)	6.32	(-9%)
k=26	9.59	12.41	(+29%)	7.90	(-18%)
k=52	14.21	16.77	(+18%)	8.33	(-41%)

All values are $\times 10^2$. pcross=0.3, pmut=0.003, G=0.8.
In parentheses is given percentage difference relative to RW.

Table 2: Comparison of Forecast Errors

(G=0.8,0.5,0.2). Forecast value under each parameter set is the average value over repetitions.

The comparison of models in out-of-sample accuracy uses two statistics: mean absolute errors (MAE) and root mean square errors (RMSE).

$$\mathbf{MAE} = \sum_{s=0}^{N_k-1} |\tilde{S}_{t+s\times 26+k} - S_{t+s\times 26+k}|/N_k,$$

$$\mathbf{RMSE} = \left\{ \sum_{s=0}^{N_k-1} [\tilde{S}_{t+s\times 26+k} - S_{t+s\times 26+k}]^2/N_k \right\}^{1/2},$$

where t is the end of the first sample period, k (= 1,4,13,26,52) is the forecast horizon, and N_k is the total number of forecasts. $\tilde{S}_{t+s\times 26+k}$ denotes the forecast values of the rate at generation $t+s\times 26+k$ and $S_{t+s\times 26+k}$ the actual rate value.

Results The results of the comparison indicate that both MAE and RMSE of AGEDASI TOF are the smallest over all horizons and all parameter sets. Table 2 contains MAE and RMSE of the three models at the five horizons under a parameter set where forecasts of AGEDASI TOF is the best. In this table, all MAE (respectively, RMSE) of AGEDASI TOF are smaller over 12% (resp., 6%) than MAE (resp., RMSE) of RW. The larger the forecast horizon, AGEDASI TOF forecasts better in comparison with the other models. This suggests that in the short term the exchange rate moves according to the trend but that in the long term the rate dynamics is related to the systematic factors such as supply and demand. Thus, the results indicate the AGEDASI TOF outperforms the other models.

4.2 An Analysis of a Bubble

As the next step of the evaluation, we analyze the real economics *quantitatively*. In order to analyze the exchange rate bubble between 1989 and 1991 in the real world, we develop out-of-sample forecast paths using AGEDASI TOF.

Methods First, AGEDASI TOF is initially trained using the rate data and the factor data in the real world through a sample period. Next, using only the fundamental factors data as explanatory variables, out-of-sample forecast paths are generated through a forecast period. In this study, the sample periods are between January 1986 and December 1987 (Week 1 - 104) and forecast periods are between January 1988 and December 1993 (Week 105 - 417). Under the best parameter(*pcross*=0.3, *pmut*=0.003, *G*=0.8)[11], the above procedure is repeated 50 times and 50 forecast paths are generated.

Results The results of out-of-sample forecast paths are divided into two groups before Week 300: a *bubble group* and a *non-bubble group* (Fig. 7). In the bubble group, the exchange rate rises around January 1989, stops around January 1991, and collapses until August 1991. In the non-bubble group, the rate moves flat without a bubble and a collapse. 42 per cent of the out-of-sample forecast paths belong to the bubble group and 58 per cent the non-bubble group[12].

We examine the bubble in our simulations in order to find plausible mechanisms of the bubble in the real world.

[11]Under this parameter setting, forecast errors are the smallest in the comparison with the random walk model and the linear regression model, as mentioned in 4.1.

[12]After 1992, the out-of-sample forecast paths have large variance. Hence, it is impossible to forecast out-of-sample over long forecast horizons. This is an important feature of nonlinear dynamics.

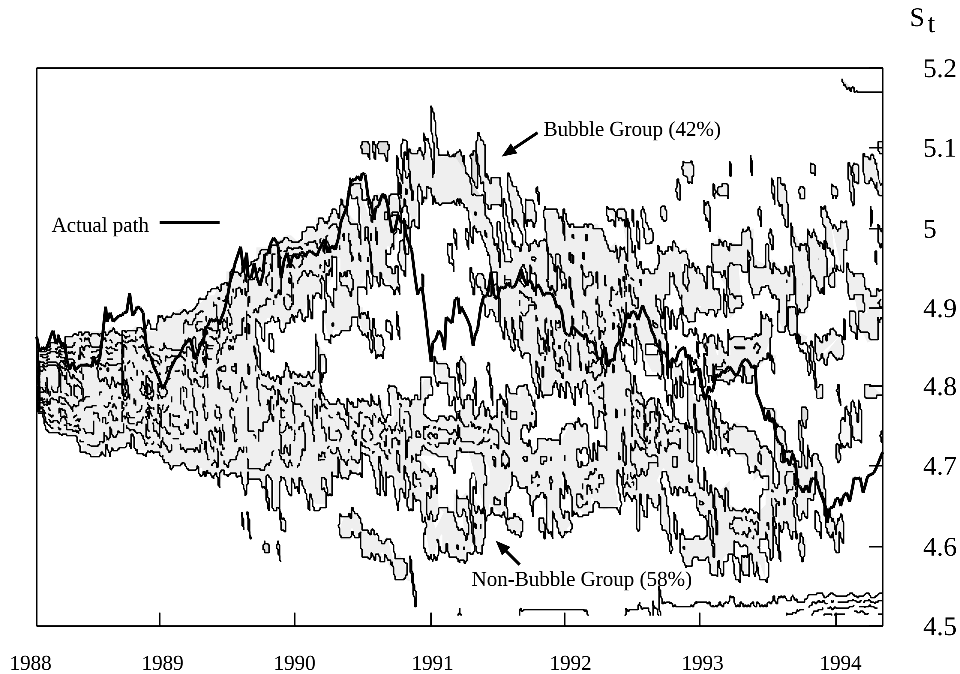

Figure 7: Distribution of Forecast Paths: Out-of-sample forecast paths pass through the dotted areas.

Market Averages of Factors' Weights First, we compare between factor's weights in a typical case of the bubble group, a *bubble case*, and in a typical case of the non-bubble group, a *non-bubble case*. In each case, market averages are calculated about factors' weights (Fig. 8). As a whole, absolute values of the market averages of the fundamentals factor's weight in the bubble case are larger those than in the non-bubble case. This implies that agents in the bubble case are more sensitive to the fundamentals factors than in the non-bubble case. In words, the start of the bubble needs the sensitivity to the fundamentals factors.

Moreover, in the bubble case, the average of Short-Term Trend Factor (ΔS_{t-1})'s weight keeps a plus value between 1989 and 1992 during the bubble and the collapse, and the average of Long-Term Trend Factor ($(S_{t-1} - S_{t-6})$)'s weight has minus value (Fig. 8). These imply that in the bubble case agents have bandwagon expectations and regressive expectations: agents expect that the recent trend is extrapolated in a short term and that a large deviation is corrected in a long term.

Supply and Demand curves and Trading Volume Next, we examine the supply and demand curves and trading volume during the bubble in the bubble case (Fig.9). When the bubble grows, demand quantity is much larger than supply quantity (Week 183,210). When the bubble stops around Week 220, the trading volume is almost zero because of the absence of supply. During the collapse after Week 220, the supply quantity is larger than the demand quantity.

Mechanism of the bubble In summary, one plausible mechanism of the bubble is considered as follows:

1. The start of the bubble is supported by the fundamental factors, on the grounds that the sensitivity to fundamental factors is necessary for the start of the bubble.

2. The bubble grows because of the bandwagon expectations: most agents expect that the short-term trends, which are caused by fundamentals factors, is continued.

3. The bubble stops because almost all agents expect the rate increase and because no one wants to sell. Then the trading volume becomes zero.

4. The bubble collapses because of the regressive expectations: the short-term trend vanishes and most agents expect that the large deviation will be corrected.

5 Conclusion

In this study, we have proposed an exchange market model with artificial adaptive agents (AGEDASI TOF)

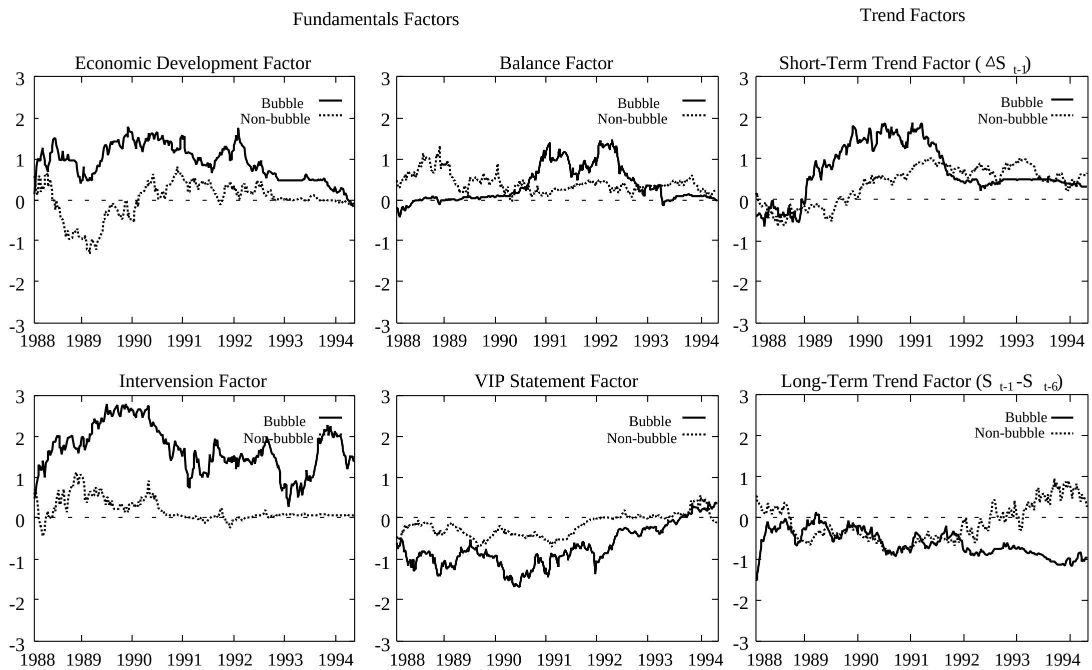

Figure 8: Market Average of Factors' Weights

and carry out computer simulations as by the *artificial market* approach. As we noted, this study is considered to be the first attempt to apply the artificial market approach to *quantitative* analysis of the real markets.

There are two differences between this model and the conventional artificial market approach models:

- While no conventional artificial market studies explicitly deal with agents' mental models of economic structures, AGEDASI TOF deals with development (adaptation) of the agents' mental models.

- While the conventional studies use only trend data, AGEDASI TOF uses both the trend data and the data about economic fundamentals and political news in the real world.

Because of these two characteristics, AGEDASI TOF can examine the rate dynamics in the real world not only qualitatively but also quantitatively, and can also analyze human behavior in the real world.

We have evaluated AGEDASI TOF in two ways:

First, we compare AGEDASI TOF with a random walk model and a linear regression model in out-of-sample forecasts. The results of the comparison is that all forecast errors of AGEDASI TOF are smaller over 12% than the other models. This indicates that AGEDASI TOF outperforms the other models over all forecast horizons.

Second, in order to analyze the exchange rate bubble between 1989 and 1991 in the real world, we have developed out-of-sample forecast paths using AGEDASI TOF. The forecast paths are divided into two groups: the bubble group and the non-bubble group. We compare factor's weights in typical cases of the bubble group and those in a typical case of the non-bubble group. This indicates that agents in the bubble case are more sensitive to the fundamentals factors than in the non-bubble case. And, we have examined the supply and demand curves and the trading volumes in the bubble case. It is found that when growth of the bubble stops, the trading volume becomes almost zero, and that during the collapse supply and demand relation is reversed.

From these results, we conclude that the bubble starts by support of fundamental factors, grows by bandwagon expectations, stops by coincidence of all agents' expectations, and collapses by regressive expectations.

This study shows that the artificial market approach is effective not only for qualitative analysis but also for quantitative analysis of economic systems in the real world.

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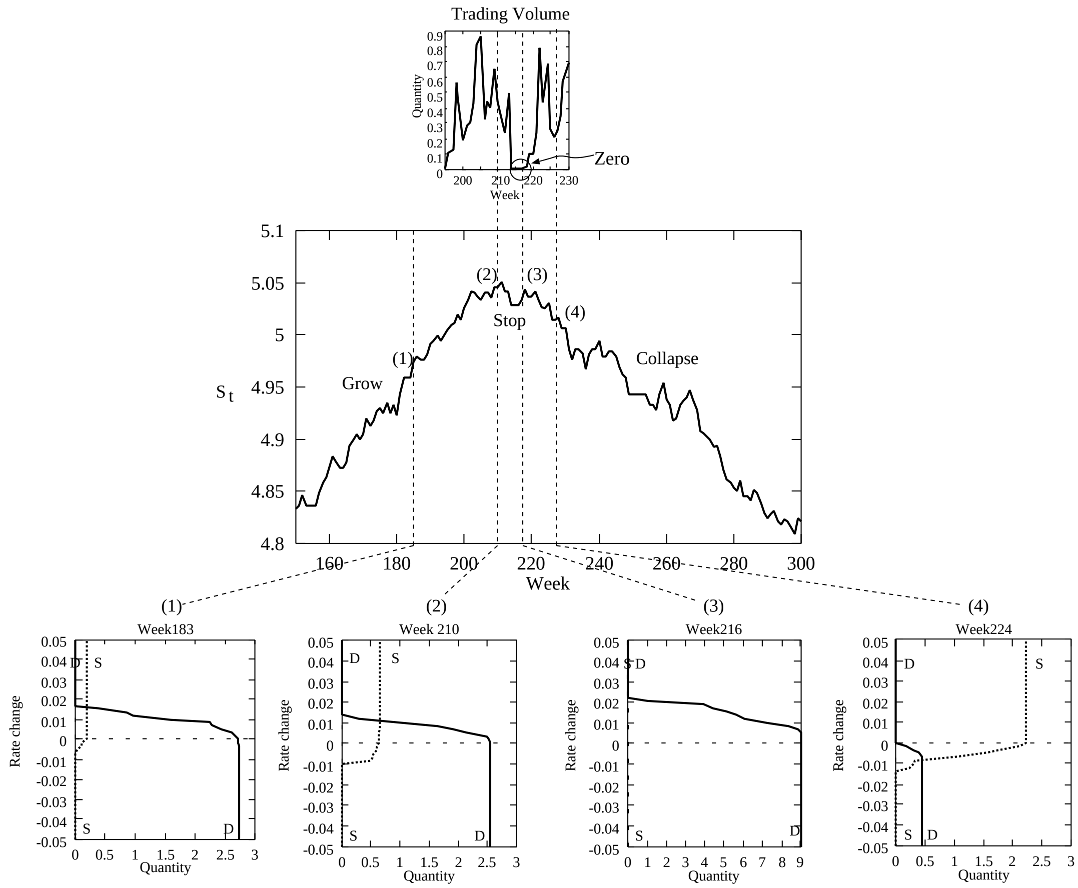

Figure 9: Supply and Demand Curves and Trading Volume

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