Emergent Phenomena in a Foreign Exchange Market: Analysis based on an Artificial Market Approach

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Abstract

In this study we propose an artificial market approach, which is a new agent-based approach to foreign exchange market studies. Using this approach, emergent phenomena of markets were explained. This approach consists of fieldwork, construction of a multi-agent model, and computer simulation of a market. The simulation results show that the emergent phenomena can be explained by a phase transition of forecast variety. This approach therefore integrates fieldwork and a multi-agent model, and provides a quantitative explanation of micro-macro relations in markets.

Introduction

Recently, large economic changes have brought to our attention the behavioral aspects of economic phenomena. One example is that large fluctuations in exchange rates are said to be mainly caused by 'bandwagon expectations'[1]. This fact shows that an exchange market has the features of multi-agent systems: autonomous agents, interaction, and emergence.

These features are related to the micro-macro problem in economics. Most conventional market models in economics, however, ignore the multi-agent features by assuming a Rational Expectations Hypothesis (REH). REH assumes that all agents are homogeneous and forbids essential differences of agents' forecasts. Recently, this assumption has been criticized and the multi-agent features have been said to be important for analysis of the micro-macro relation in markets.

Among several alternative approaches, there are *multi-agent* models. These model the market with artificial adaptive agents and conduct computer simulations. There are, however, two problems in the multi-agent models constructed up to now. First, they do not reflect the results of fieldwork studies about behavioral aspects of agents. Second, they do not use actual data series about economic fundamentals and political news. They can not, therefore, investigate the actual exchange rate dynamics quantitatively.

[1]The word "bandwagon" here means that many agents in a market ride along with the recent trend.

The purpose of this study is to propose a new agent-based approach of foreign exchange market studies, an *artificial market approach*. This approach integrates fieldwork and multi-agent models in order to provide a quantitative explanation of the micro and macro relation in markets.

Framework of the Artificial Market Approach

The artificial market approach is divided into three steps. First, *fieldwork;* field data of actual dealers' behavior are gathered by interviews. As a result of analysis, hypotheses are proposed about the dealers' behavioral pattern. Second, *construction of a multi-agent model;* a multi-agent model of the market is implemented based on these hypotheses. The model provides linkage between the behavioral pattern of agents at the micro level and the rate dynamics at the macro level. Third, *analysis of emergent phenomena;* in order to evaluate the model, we conduct simulations using actual data of economic fundamentals. Based on the simulation results, we verify whether the model can explain emergent phenomena of an actual market.

This approach has two advantages over previous studies. First, a multi-agent model in this approach reflects the results of fieldwork, because the model is constructed on the basis of observations of dealers' behavior, and because actual data about economic fundamentals and news are used in the simulation. Next, the model is evaluated at both the micro and macro level. At the micro level, the behavioral patterns of agents in the model are compared with those of the actual dealers in the field data. At the macro level, it is verified whether the model can simulate the emergent phenomena of rate dynamics in the real world. These advantages of the artificial market approach are necessary for a quantitative analysis of the micro-macro relation the actual markets.

Fieldwork

We observed the actual dealers' behavior by interviews and proposed a hypothesis of dealers' learning, which is used in the construction of the multi-agent model.

Interview Methods We held interviews with two dealers who usually engaged in yen-dollar exchange transactions in Tokyo foreign exchange market. We asked each dealer to do the following with respect to the rate dynamics from January 1994 to November 1995: To divide these two years into several periods according to their recognition of the market situations, to talk about which factors they regarded as important in their rate forecasts in each period, to rank the factors in order of weight (importance), and to explain the reasons for their ranking. When they changed the ranking between periods, to explain the reasons for the reconsideration.

Results From the interview data, we found three basic features in the acquisition of prediction methods in the market. First, there are fashions in the interpretation of factors in the markets, which are called *market consensus*. Second, the dealers communicated with other dealers to infer a new market consensus, and replaced (part of) their prediction method with that of other dealers which better explained recent rate dynamics, when switching prediction method. Finally, large differences between forecasts and actual rates promoted a change of each dealer's opinion. For example, in July 1995, when the rate reached the level of 92 yen, one dealer suddenly recognized that the trend had changed. He then discarded his old opinions about factors and adopted new opinions.

From the above features, we propose the following hypothesis at the micro level in markets. *When the forecasts based on a dealer's own opinion markedly differs from the actual rates, each dealer replaces (part of) their opinions about factors with other dealers' successful opinions.* This hypothesis implies that the learning pattern of actual dealers is similar to the adaptation in ecosystem. In our multi-agent model, the adaptation of agents in the market will be described with genetic algorithm, which based on ideas of population genetics.

Construction of a Multi-agent Model

Using weekly actual data, the proposed model iteratively executes the five steps (Fig.1 and Fig.2).

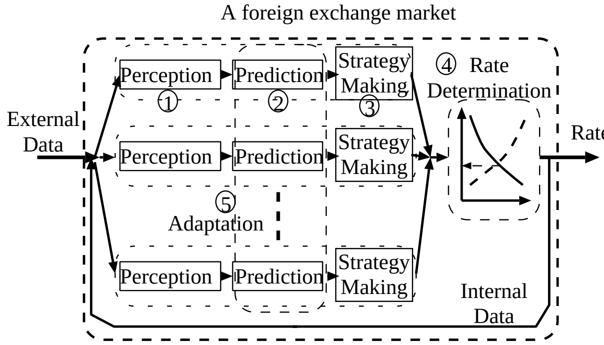


Figure 1: Framework of model.

STEP 1: Perception Each agent first interprets raw data and perceives news about factors affecting the yen-dollar exchange rate. The news data are made by coding the weekly change in 17 data streams[2]. Those values range discretely from -3 to $+3$[3]. *External data* are defined as the data of economic fundamentals or political news (No.1-14). *Internal data* are defined as data of short-term or long-term trends of the chart (No.15-17).

STEP 2: Prediction Each agent has his own weights of the 17 data, whose values range among nine discrete values $\{\pm3, \pm1, \pm0.5, \pm0.1, 0\}$. After receiving the data, each agent predicts the rate fluctuation of the coming week by using the weighted average of the news data in this week as well as equations (1) and (2) in Fig. 2.

STEP 3: Strategy Making Each agent has dollar assets and yen assets. Each agent decides, on the basis of his or her own prediction, the trading strategy (order to buy or sell dollar) according to Equations (3), (4), and (5) in Fig. 2. The trader then maximizes his negative exponential utility function[4] of his expected return of the following week.

STEP 4: Rate Determination After the submission of orders, the demand (resp., supply) curve is made by the aggregation of orders of all agents who want to buy (resp., sell). The demand and supply then determine the equilibrium rate, where supply and demand just balance.

STEP 5: Adaptation In our model, different agents have different prediction methods (combinations of weights). After the rate determination, each agent improves his prediction method using other agents' predictions. Our model uses GAs to describe the interaction between agents in learning.

A chromosome is a string of all weights of one agent, that is, the trader's prediction method. The fitness value reflects the forecast accuracy of each prediction method as per Equation (7) in Fig. 2. Our model is based on Goldberg's simple GA[5]. The selection operator is economically interpreted as the propagation of successful prediction methods. The crossover operator works like the agent's communication with other agents, and the mutation operator works like independent changes of each agent's prediction method.

[2] The 17 data are 1. Economic activities, 2. Price, 3. Interest rates, 4. Money supply, 5. Trade, 6. Employment, 7. Consumption, 8. Intervention, 9. Announcement, 10. Mark, 11. Oil, 12. Politics, 13. Stock, 14. Bond, 15. Short-term Trend 1 (Change in the last week), 16. Short-term Trend 2 (Change of short-term Trend 1), and 17. Long-term Trend (Change through five weeks).

[3] Plus (minus) values indicate that the data change causes dollar depreciation (appreciation) according to traditional economic theories.

[4] Equation (3) is calculated by using this function.

[5] The percentage of selection is called the *generation gap*, G. A single-point crossover (mutation) operation occurs with probabilities p_{cross} (p_{mut}).

5.20 Transaction amount Quantity

Example (Week t, Logarithm of last week's rate = 5.20)

STEP 1: Perception

This week's news data (common to all agents).

Interest	Trade	Stock	Trend
++	−	− − −	++

STEP 2: Prediction

Agents **i**'s weights.

+0.5	−0.5	+0.1	+3.0

Agent **i**'s forecast:

$$\textbf{Mean} = \text{trunc}\{\textstyle\sum(\text{Weight} \times \text{News})\} \times \text{scale} \quad ...(1)$$

$$=\text{trunc}\{(+2)\times(+0.5)+(-1)\times(-1.0)+(-3)\times(+0.1)+(+2)\times(+3.0)\}\times 0.02 = +7\times 0.02 = \mathbf{+0.14} \leftarrow \text{Rise from 5.20}$$

$$\textbf{Variance}^{-1} = \sqrt{\{\textstyle\sum(\text{Weight} \times \text{News} > 0)\}^2 - \{\sum(\text{Weight} \times \text{News} < 0)\}^2} \quad ...(2)$$

$$= \sqrt{\{2 \times +0.5 + (-1) \times (-1.0) + 3 \times 2.0\}^2 - \{-2 \times 0.1\}^2}$$

$$= \mathbf{8.00}$$

STEP 3: Strategy Making

Optimal amount of agent **i**'s dollar asset

= (Forecast mean) / (Forecast variance) ...(3)

= +0.14× 8.00 = +1.12

Agent **i**'s order quantity

= (Optimal amount) − (Last week's amount) ...(4)

= +1.12 − (−0.74) = +1.86 (Buy)

(+ : Order to buy, − : Order to sell.)

Agent **i**'s strategy

$$= \begin{cases} 1.86 \text{ (Buy)} & \text{(If rate} \leq +0.14) \\ \text{No Action} & \text{(If rate} > +0.14) \end{cases} \quad ...(5)$$

Each agent orders to buy (resp., sell) when the rate is lower (resp., higher) than his forecast mean.

STEP 4: Rate Determination

STEP 5: Adaptation

Agent **i**'s Chromosome $=\{+\mathbf{0.5}, -\mathbf{1.0}, +\mathbf{0.1}, +\mathbf{3.0}\}$ ...(6)

Agent **i**'s Fitness

= −| (Forecast mean)−(Rate change)| ...(7)

$= -|(+0.14) - (+0.50)| = \mathbf{-0.36}$

⇓ **GAs** (Selection,Crossover,Mutation)

New weights

⇓

STEP 1 in the Next Week t+1

Figure 2: Algorithm.

After the Adaptation Step, the week ends and our model proceeds to the next week's Perception Step.

Analysis of Emergent Phenomena

In order to examine the emergent phenomena of markets, we conducted extrapolation simulations of the rate dynamics from January 1994 to December 1995.

Simulation Methods

We repeated the following procedure a hundred times in order to generate a hundred simulation paths[6] First, the initial population is a hundred agents whose weights are randomly generated. Second, we trained our model by using the 17 real world data streams from January 1992 to December 1993[7]. During this *training period*, we skipped the Rate Determination Step and used the cumulated value of differences between the forecast mean and the *actual rate* as the fitness in the Adaptation Step. Finally, for the period from January 1994 to December 1995 we conducted the extrapolation simulations. In this *forecast period*, our model forecasted the rates in the Rate Determination Step by using only external data. We did not use any actual rate data, and both the internal data and the fitness were calculated on the basis of the rates generated by our model.

Overview of Results

The simulation paths are divided into two groups: the *bubble group*, in which the paths have a quick fall and a rise (a rate bubble) (Fig. 3a), and the *non-bubble group*, in which the paths don't have such a bubble (Fig. 3b)[8]. The movement of the actual path is similar to that of the mean path of the bubble group. On the other hand, the path extracted by linear regression using the external data of our model moves in a way similar to that in which the mean path of the non-bubble group moves.

Phase Transition of Forecast Variation

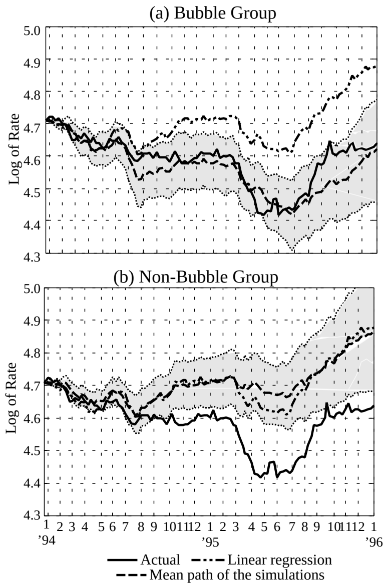
In order to analyze any emergent phenomena, we examine a phase transition in the agents' forecast variability (variation) in the simulated paths. We analyze five simulation paths randomly selected from the bubble group. Because the pattern of these results are common among the selected five paths, we illustrates the results of one typical path.

Flat Phase and Bubble Phase Each simulated path in the bubble group is divided into two phases: The period with small fluctuations(Mar.'94 - Dec.'94) is termed

[6] We used the parameter sets (p_{cross}=0.3, p_{mut} =0.003, G=0.8). The simulation suffered from the smallest forecast errors by using this set in our previous study.

[7] Each weekly time series was used a hundred times, so in this training period there were about ten thousand generations.

[8] The bubble group occupies 25% of all the simulation paths. The non-bubble group occupies 75%.



The dotted areas denote the mean ± one standard deviations.

Figure 3: Distribution of simulation paths.

the *flat phase* while the period with large fluctuations (Jan.'95 - Dec.'95) is termed the *bubble phase*.

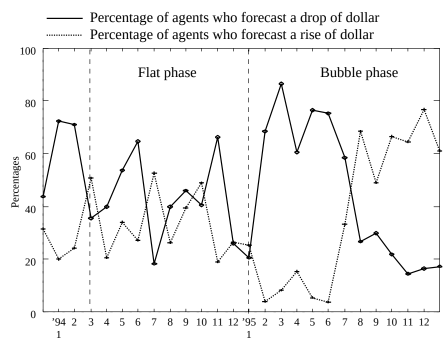


Figure 4: Percentages of agents' forecasts

Fig. 4 shows the percentage of forecasts of rise and drop of the dollar, in the form of four weeks averages. In the flat phase, the variation among forecasts is rich because there are forecasts on both sides. In the bubble phase, the variation among forecasts is poor because most agents agree.

In the flat phase, because there is sufficient supply and demand at or around last week's rate, supply and demand tend to meet around the the last week's rate, (i.e., the rate fluctuation is small), and the trading amounts are larger at the equilibrium point. In contrast, during the bubble phase, the supply and demand are one-sided, so the trading amounts are smaller at the equilibrium point. Supply and demand tend to meet away from the previous week's point because there are not enough opposite orders at last week's equilibrium rate. Hence, the rate fluctuation tend to get larger.

Mechanism of Phase Transition In order to determine the mechanism behind the phase transition, we need to investigate the dynamic patterns of the agent's weights.

First, the weights are classified by a factor analysis. The matrix which is analyzed is a list of 12 weights[9] of 100 agents every 10 weeks. As a result, six factors are extracted[10]. Weights of Economic activities and Price data have the largest loading value of the first factor. We call the first factor *Price monetary* factor, because these two data are used by the price monetary The second factor has relation to Short-term trends and Stock data, so we call it *Short-term* factor. The third, to Trade and Interest rate data, which are included in the portfolio balance approach in econometrics, so we call it *Portfolio balance* factor. The forth, to Announcement and Employment data, so we call it *Announcement* factor. The fifth, to Intervention, Politics, and Employment data, so we call it *Politics* factor. The sixth, to Long-term trend data, so we call it *Long-term* factor. Moreover, according to their meanings we divide these six factors into the three categories. Price monetary and Portfolio balance factor are classified into *Econometrics category*. Announcement and Politics factor, into *News category*. Short-term and Long-term factor, into *Trend category*.

Next, for each category, the dynamics of its weight is examined. First, the weights of Econometric category are relatively stable, however, its absolute value is so small that the influence on rates is not so large. Only Portfolio balance factor has large absolute values during the bubble phase. Second, the very strong market consensus about News category is established just before the bubble phase started. Finally, because of the large correlation before the bubble started, the weights of the trend category got larger in the bubble phase. The plus weights of Trend category mean that agents forecast that the trend in the future will be the same as the recent trend. Therefore, the upward (downward) trend of dollar makes demand (supply) of dollar. The demand (supply) makes the following upward (downward) trend, and so on. It is defined as *positive feedback*. However, at the end of the bubble phase, this positive feedback weakened because the weight of the long-term data changed into negative territory. After the rate passed its lowest point in May '95, the correlation coefficients became much smaller. A lack of opposing orders thus led the forecasts using the trend data to fail.

In summary, we propose the following mechanism to explain the transition between phases. First, in the flat phase, there are varying opinions with respect to the News and Trend category. This leads to large trading

[9]Five time series are discarded because they are alway zero or both their market average and variance are too small.

[10]The proportion of explanation is 67.0 %.

amounts and small exchange rate fluctuations. Second, in the later half of the flat phase, many agents focus on Trade, Announcement, and Politics data. Third, a convergence of opinions with respect to these data and a positive feedback of Trend factors ushered in the bubble phase, which leads to small trading amounts and large rate fluctuations. Fourth, in May 1995, almost all forecasts in the market converged. Because there were no opposing orders in the market, the downward trend vanished. Finally, after the rate passed its lowest point in May 1995, the weight of the long-term data became negative, and the positive feedback was weakened. Thus, the bubble phase ended.

Departure from Normality Many statistical studies reveal that the distribution of rate changes is different from normal distribution. The rate changes in the simulations of the bubble group also have peaked, long tailed (i.e., leptokurtic) distributions not unlike the actual rate. In fact, the kurtosis of a typical simulation in the bubble group (0.477) is close to that of actual rate changes (0.564)[11]. The mechanism giving rise to such a leptokurtosis can be explained by the phase transition. The distribution of rate changes in the bubble phase has a large variance (long tailed distribution), while the flat phase has a small variance (peaked distribution). Combining these two distributions gives rise to a distribution of rate changes that is peaked and long tailed.

Volume and Fluctuation Previous statistical studies also show that there is negative correlation between trading volume and rate fluctuation. Namely, when the rate fluctuates more, the volume is smaller. Contrariwise, when the rate turns flat, the volume becomes larger. Also, a typical simulation shows a significant negative correlation, -0.2800. This negative correlation can be explained as follows: In the bubble phase, many agents forecast changes in the same direction. The rate movement continues in that direction for many weeks and rate fluctuations are amplified. However, the transaction amount drops because the order quantity in the other direction is small. In contrast, in the flat phase, because there is a sustaining amount of both supply and demand around last week's equilibrium rate, trading amounts are larger at equilibrium, but rates fluctuate less.

Contrary Opinions Phenomenon Many dealers and their books say, " If almost all dealers have the same opinion, the contrary opinion will win." In fact, field data sometimes show that convergence of dealers' forecasts leads to an unexpected result in the rate change. Also in typical simulations, in May 1995, when almost all the agents' forecasts converged to the same forecast in the same direction, the rate did not move in that direction. As mentioned, this is caused by the fact that there are no orders in the opposite direction and no transactions can occur.

[11] The kurtosis is 0.0 for a normal distribution.

Conclusions

We proposed an artificial market approach and analyzed three emergent phenomena in markets. First, the a transition between phases of agents' forecast variety (variation among forecasts) in the simulations was examined. As a result, a mechanism for these transitions was proposed: convergence of opinions about news factors and trade factors, and positive feedback by trend factors caused the phase transition. Second, based on these concepts, we explained certain emergent phenomena. The long-tailed and peaked distribution of rate changes was explained by combining the long-tailed distribution in the bubble phase and the peaked distribution in the flat phase. Negative correlation between trading volume and rate fluctuations was explained by their negative relation in the two phases. The phenomenon of 'Contrary opinions' was explained by the lack of opposite orders when all agents' forecasts converged.

The artificial market approach therefore explained the mechanisms of the emergent phenomena at the macro level by a hypothesis about the learning rules at the micro level, that is, this approach provides a quantitative explanation of the micro-macro relation in markets both by integration of fieldwork and a multi-agent model, and by using actual data about economic fundamentals and news.

References

de la Maza, M. and D. Yuret. 1994. A futures market simulation with non-rational participants. In *Artificial Life IV*, edited by R.A. Brooks and P. Maes. Cambridge, MA: MIT Press, p. 325–330.

Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning.* Addison-Wesley Publishing Company.

Izumi, K. and T. Okatsu. 1996. An artificial market analysis of exchange rate dynamics. In *Evolutionary Programming V*, edited by L.J. Fogel, P.J. Angeline, and T. Bäck. Cambridge, MA: MIT Press, p. 27–36.

Palmer, R. G., W. B. Arthur, J. H. Holland, B. LeBaron, and P. Taylor. 1994. Artificial economic life: A simple model of a stock market. *Physica D*, 75: 264–265.