An Artificial Market Model of a Foreign Exchange Market

Kiyoshi Izumi[1]

Department of General Systems Studies,

Graduate School of Arts and Sciences,

the University of Tokyo

[1]This research was partially supported by JSPS Research Fellowships for Young Scientists.

Abstract

In this study, we proposed a new approach to foreign exchange market studies, an *artificial market approach*. The artificial market approach integrated fieldwork studies and multiagent models in order to explain the micro and macro relation in markets.

The artificial market approach has the three steps:

First, in order to investigate the learning patterns of actual dealers, we carried out both interviews and questionnaires. These field data made it clear that each dealer improved his or her prediction method by replacing (a part of) his or her opinions about factors with other dealers' opinion which can forecast more accurately.

Second, we constructed a multiagent model of a foreign exchange market. Considering the result of the analysis of the field data, the interaction of agents' learning is described with genetic algorithms in our model.

Finally, the emergent phenomena at the market level were analyzed on the basis of the simulation results of the model. The results showed that rate bubbles were caused by the interaction between the agents' forecasts and the relationship of demand and supply. The other emergent phenomena were explained by the concept of the phase transition of forecast variety. The filed data also supported this simulation results.

This approach therefore integrates the fieldwork and the multiagent model, and provides quantitative explanation of the micro-macro relation in markets.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In May 1995 the yen-dollar exchange rate dropped dramatically and broke the level of 80 yen for the first time. In May 1997 the yen-dollar rate reversed to 126 yen. During the only two years the yen-dollar rate increased over 50%. Exchange rates sometimes show such unexpectable moves. Some dealers and analysts say, "Only markets know."

Recently the large economical changes have called our attention to the psychological or behavioral features in economic phenomena. One typical example is the above mentioned large fluctuation of exchange rates. A large fluctuation (a rate bubble) is said to be mainly caused by bandwagon expectations[1] [68]. This fact shows that an exchange market has some features of multiagent systems. *Autonomous Agents*, each dealer makes a decision based on his own trading rules and information. *Interaction*, each dealer learns market situation interacting with each other. *Emergence*, there are e-

[1] The word "bandwagon" here 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.

mergent phenomena such as rate bubbles at the upper (market) level, which are not directly designed at the lower (agent) level.

These multiagent features are related to the micro-macro problem in economics. Because agents in economic systems interact with each other, there are complex relations between the *micro* behavior of agents and the *macro* behavior of whole systems. In complex economic systems, agents should be *adaptive* to the change of whole systems: they must always change their own mental models of economic systems in order to improve their prediction.

Surprisingly, Keynes already stressed the interaction of prediction in a market in his famous description of investment [77].

> Professional investment may be linked to those newspaper competitions in which the competitors have to pick up the six prettiest from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of competitors as a whole; so that each competitor has to pick not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view.

However most conventional economic theories of exchange markets ignore the multiagent features by assuming a Rational Expectations Hypothesis (REH). REH assumes that all agents are homogeneous and forbids essential differences of agents' forecasts. Namely REH permits only non systematic d-ifferences (noises) which distribute in the normal distribution. By this strong assumption, REH avoids describing agents' adaptive behavior. Recently, this avoidance has been criticized and the multiagent features have been said to be very important for analysis of emergent phenomena in markets. Therefore, alternative approaches apart from REH which describe agents' adaptive behavior, are said to be necessary.

Several alternative approaches are proposed. Among them, there is a *multiagent* approach [4, 36, 64, 86, 98, 104]. Previous studies based on this approach, make market models with artificial adaptive agents and conduct computer simulations. Then they analyze the evolution of models and use the results of the analysis to understand the actual markets.

There are, however, two problems in the previous multiagent models. First, they do not incorporate mental models of dealers. Hence they do not reflect the results of fieldwork studies about the perception and prediction process of dealers. Second, the previous studies do not uses actual data series about economic fundamentals and political news. They can, therefore, investigate the actual rate dynamics only qualitatively not quantitatively.

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

In this approach, first, some hypotheses at the agent level are proposed on the basis of field data about dealers' learning and interaction in the real markets. From the field data, we found the similarities between population dynamics in biology and dynamics of dealers' opinions in markets. We thus propose hypotheses of agents' learning patterns, based on the analogies with population dynamics in biology.

Second, a multiagent model is constructed based on the hypotheses about mental models of dealers. The model would be more realistic than the traditional economic models. In our present study, the multiagent model uses genetic algorithm in order to describe population dynamics of agents' opinions. This model is named **A GE**netic-algorithmic **D**ouble **A**uction market **SI**mulation in **TO**kyo **F**oreign exchange market (AGEDASI TOF[2])

Finally, emergent phenomena at the market level are analyzed using the simulation results of the model in order to evaluate the model. The emergent phenomena which were analyzed in this study are rate bubbles, contrary opinions, rate change distribution apart from normality, and negative correlation between trading amounts and rate fluctuation. These can be explained using the idea, *phase transition of forecast variety.*

The plan of this study is as follows. In chapter 2, we briefly review the theoretical backgrounds of exchange market studies from the viewpoint of the micro-macro problems. In chapter 3, we show framework of the artificial market approach. The detailed description of the artificial market approach is shown in chapter 4, chapter 5, and chapter 6. In chapter 4, we analyze our interview and questionnaires with dealers in Tokyo foreign exchange market in order to investigate the features of agent behavior. From this observation at the micro level, we propose some hypotheses about dealers' behavior. In chapter 5, we propose a new multiagent model of the market using genetic algorithms (GAs). In chapter 6, we conduct simulations using our model to analyze the emergent phenomena of the real market, in order to evaluate our model. In chapter 7, several points about the artificial market approach are discussed. In chapter 8, this paper is concluded.

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

Chapter 2

Theoretical Background

2.1 Overview

The relation between "micro" and "macro" is one of the most complicated but important topics in contemporary economic theory[1]. Assumptions of economic agents' rationality, which is frequently adopted in economics, allow economic theories to avoid to throughly investigate how the economic phenomena at the macro level emerge from the economic agents' behavior at the micro level. This is true in case of foreign exchange market studies.

The main purpose of foreign exchange market studies is to figure out the relation between inputs and outputs of the market. The output of the market is the foreign exchange rate such as yen-dollar rate. The inputs are various information relevant to the rate dynamics. For example, economic indices such as money supply, interest rates, trade balance, and price indices.

Conventional studies of the foreign exchange markets are divided into two

[1] Of course, it is important also in other fields.

types: macro level studies and micro level studies (Fig. 2.1).

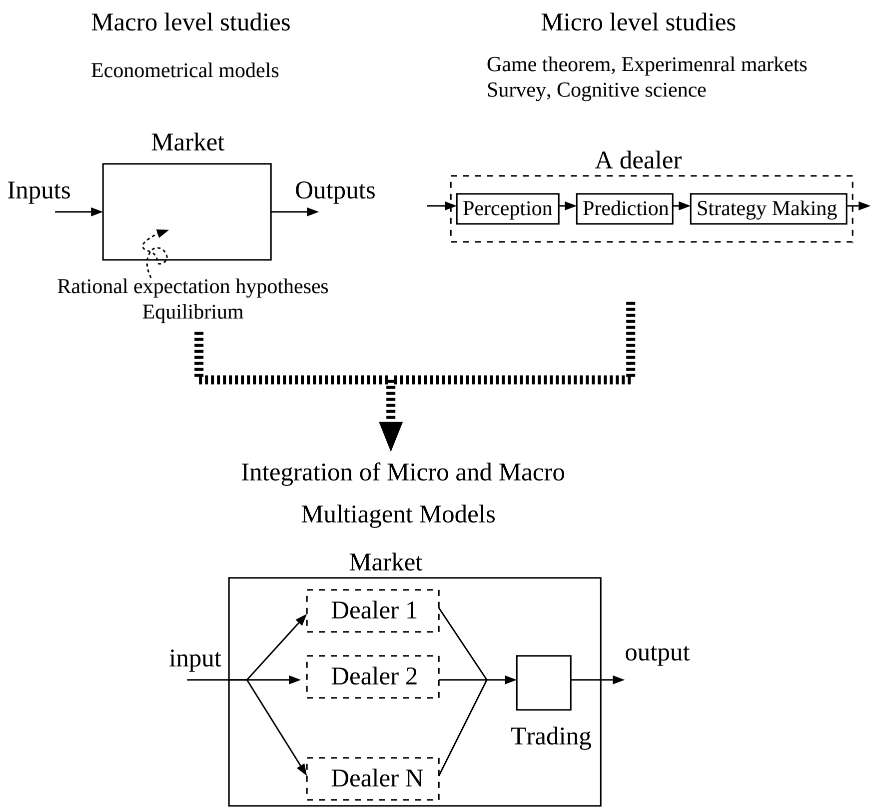


Figure 2.1: Overview of exchange market studies.

The macro level studies such as many econometric models and time series models, deal with only macro variables (inputs and outputs of the market system). They don't explain the internal mechanism of the market in their reduced form models. Recently many scholars criticize both theoretically and empirically such ignorance of the interaction and leaning of market participants.

The micro level studies such as game theoretic models and survey studies, treat information processing and/or decision making process of each participant. However, these studies neither propose nor describe efficient linkage between behavior pattern at the micro level and input-output relation at the macro level.

A new approach, *multiagent models*, appears in these years. This approach is inspired from artificial life studies and tries to integrate the micro and macro levels. However previous multiagent models of markets have some problems for analysis of the real markets.

This chapter is planed as follows. First, we explain the models of macro level studies and point out their problems in section 2.2. Second, we overview the micro level models and theories in section 2.3. Finally, we introduce the new approach, multiagent models, and explain their problems in section 2.4.

2.2 Macro Level Studies

The macro level studies deal with only macro variables, inputs and outputs of the market system (fig. 2.2). Many econometrical models of markets are contained by them. Their main purpose is to capture relevant inputs and to find optimal coefficients of the inputs. Namely they assume the existence of the *one static correct* relation between the inputs and outputs. Although they seek the correct relation, they explicitly describe neither why the relation exists, how it establishes, nor whether it changes in the course of time. They don't explicitly explain the internal mechanism of the market, such as interaction of agents and learning mechanism, in their reduced form models. Especially, they neglect interaction and learning of market participants because of the two assumptions: equilibrium and rational expectation hypotheses (REH). We explain these assumptions in section 2.2.1 and 2.2.2 respectably.

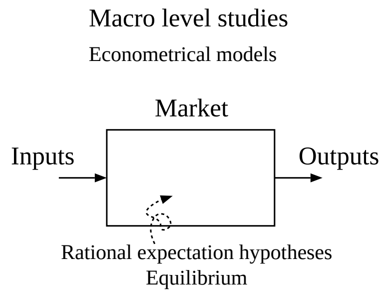


Figure 2.2: Framework of macro studies

2.2.1 Equilibrium

Each agent in foreign exchange markets can submit his desirable rates(*order rates*) and quantities(*order quantities*) to buy or sell currencies. Offers to buy are called *bids* and offers to sell *asks*. If bids or asks are accepted by other agents, exchange is executed. One important feature of the foreign exchange markets is that both buyers and suppliers can propose their order rates. Such markets are called *double auction markets* [50].

Ordinally in markets, as a price is higher, quantity of demand decreases and quantity of supply increases (Fig. 2.3). Therefore, there is at least one point where the demand curve and the supply curve cross. A price of this point is called an *equilibrium price* and a quantity of this point is called an *equilibrium quantity*.

For sellers, a buyer with a higher price is a “better” buyer. Conversely for buyers, a seller with a lower price is a “better” seller. Hence, exchanges execute between buyers with higher prices and sellers with lower prices than an equilibrium price.

The concept “equilibrium” can be applied to foreign exchange markets. In this study, it is assumed that rates of foreign exchange markets are decided

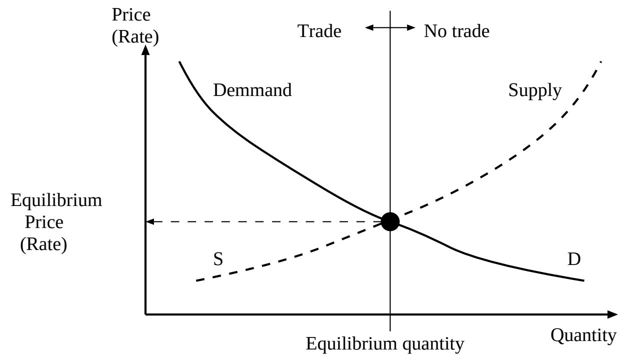


Figure 2.3: equilibrium of the market

to the equilibrium rates.

2.2.2 Rational Expectations Hypothesis (REH)

Assumptions

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

Assumption 1: In the Perception step, all agents are the same. That is, all agents have complete information.

Assumption 2: In the Prediction step, all agents are the same. That is, all agents have the same model of the economic system.

Assumption 3: In the Strategy Making step, all agents are the same. That is, all agents select their optimal behavior maximizing their utilities.

Assumption 4: 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[2] the same. Therefore, REH can avoid describing agents' adaptive behavior.

The REH approach of modeling a foreign exchange market is illustrated as follows.

Based on several economic conditions, REH models assumed that an exchange rate is determined by reduced-form equation:

$$S_t = \mathbf{x}_t + b\mathbf{E}_t[S_{t+1}] \tag{2.1}$$

,where S_t is the logarithm of the exchange rate and $\mathbf{x}_t$ the exogenous variables (also called *fundamental variables*) that are related to the rate change. $\mathbf{E}_t[S_{t+1}]$ is the expectation that the "average" agent holds at period **t** about next period's exchange rate.

It should be noted that kinds of the exchange variables depends on what economic structure is considered. For examples, in the monetary model of the exchange rate, $\mathbf{x}_t$ include the supply of money, the price level, and the interest rate: the portfolio balance model adds the value of bonds to the above exogenous variables.

The assumptions of REH has the following implication. The expectations of all agents are essentially identical to the "average" agent's expectation, i.e. "tend to be distributed, for the same information set, about the prediction of the theory" [94]. Thus, agents' expectations which hold at period **t** about period **t+k**'s rate, are deduced from the following rule:

$$\mathbf{E}_t[S_{t+k}] = \mathbf{E}_t[\mathbf{x}_{t+k}] + b\mathbf{E}_t[S_{t+k+1}] \tag{2.2}$$

[2]If any differences exist, they are caused by only random factors [94].

This equation can be seen as a difference equation of the first order. The solution can be written in the following form:

$$\mathbf{E}_t[S_{t+k}] = \sum_{i=0}^{\infty} b^i \mathbf{E}_t[\mathbf{x}_{t+k+i}] + C_t \left(\frac{1}{b}\right)^k \tag{2.3}$$

,where C_t is an arbitrary constant satisfying:

$$C_t = \left(\frac{1}{b}\right) C_{t-1}. \tag{2.4}$$

By substituting the equation (2.3) into the equation (2.1), the following solution of S_t is obtained:

$$S_t = \sum_{i=0}^{\infty} b^i \mathbf{E}_t[\mathbf{x}_{t+i}] + C_t. \tag{2.5}$$

The second term of this solution has been called a *rational speculation bubble*[3].

The solution implies that the exchange rate is equal to the present value of the whole expected future path of the exogenous variables $\mathbf{x}_{t+i}$.

Problems

There are some problems in REH. Some problems are theoretical: these problems take place because REH assumes that expectations of all agents essentially identical. The other problems relate to REH's empirical verification.

Theoretical problems REH assumes that expectations of all agents essentially identical. Hence, the REH models face with following theoretical

[3] C_t is used to be set to zero in the REH literature.

problems.

1. It is difficult that all the above assumptions are satisfied in actual economy because the assumptions are too strong and unrealistic.

2. REH models produce an infinite number of paths. But it is undecided which path will take place actually.

3. REH models can't explain various emergent properties, as below, which are observed in the real markets.

   Rate Bubbles Rate bubbles[4] and collapses are not explained from micro level: the rational speculative bubble C_t is an "arbitrary" constant, which is introduced *ad hoc* without micro level explanation.

   Departure from normality Many statistical studies reveal that the distribution of rate changes is different from normal distribution [10,18,102,103]. That is, exchange rate changes have peaked, long tailed (i.e. leptokurtsis) distributions. REH however needs that the distribution of rate changes is normal distribution.

   Auto Correlation Many statistical studies also reveal that exchange rate changes are not necessarily independent, identically distributed (iid) [10, 81, 82]. Especially, there is indeed evidence of auto-correlation of rate changes and rate variance. REH however needs that rate changes are iid.

[4]Many econometric studies define bubbles as departure from the level which is determinated by the economic fundamentals. We however define bubbles as sudden large rises or falls of the rate, stops of such boosts, and sudden returns to the original level.

Large Trading Volume If the REH assumptions are satisfied, there are few opportunities to earn profits by speculation. Hence, trading volume is always small. However, the real market has larger trading volume than REH expected [117].

Negative Correlation between trading volume and rate fluctuation There is negative correlation between trading volume and rate fluctuation [115,116]. Namely, when the rate fluctuates more, the volume is smaller. When the rate moves flat, the volume is larger. REH models can't explain such negative correlation.

Contrary Opinions Phenomenon Many dealers and their books say, " If almost all dealers have the same opinion, the contrary opinion will win." [59, 115, 116] In fact, survey data sometimes show that convergence of the dealers' forecasts leads to an unexpected result of the rate move. REH models can't explain such a phenomenon.

Empirical problems Recent empirical tests have revealed that REH models do not coincide with actual data.

1. Most exchange rate movements appear to occur in the absence of observable change of fundamental variables [83]. In other words, there is cause of the rate change unrelated to the change of fundamental variables.

2. REH implies that there is a long-run equilibrium relationship between the rate and the fundamental variables [1, 11, 18]. The cointegration tests can be used to verify that kind of equilibrium relationship. All of the results of cointegration tests reject the null hypothesis of a

long-run equilibrium relationship between the rate and the fundamental variables.

3. There are studies on the expectation formation of actual agents, based on survey data [47,51,68,71,113]. In short, the result of these studies is that expectations over short horizons are not consistent with that over long horizons: the expectations over short horizons tend to incorporate band wagon effects[5] and that over long horizon display regression[6] property.

4. Many studies test REH models' validity by determining how well they perform out-of-sample, compared with alternative models such as the random walk [89, 92]. The principal result is that REH models fail to outperform the random walk model.

Departure from REH

REH models face with many problems both theoretically and empirically. When we abandon the assumptions of REH, we must take another approach.

To find another approach, we will get back to consider actual economy. In actual economy, each agent predicts future movement of an economic system and behaves according to his own prediction. So to speak, he is an "econometrician". Then, aggregated behavior of agents moves whole economic system. In accordance to this movement of the economic system, each agent changes his way of prediction. We call this change of the way of prediction *learning*.

[5] It is called as a *bandwagon effect* that agents expect that the most recent trend is extrapolated.

[6] It is called as *regressive property* that agents expect that large deviation is corrected.

Learning in a market is like playing tag; when players (agents) pursue an it (whole economic system), the it moves influenced by players' moves. In the point of view of this interaction with environments, it also can be called *adaptation*.

Because REH models have the above problems, recently it is said that economic models apart from REH are needed. These models must apply concrete learning algorithm in order to describe decision making process of agents. As one experimental trying, this study applies genetic algorithm.

2.3 Micro Level Studies

The micro level studies treat information processing and/or decision making process of each participant. Especially they refer to perception, prediction, or strategy making mechanism of dealers (fig. 2.4). The perception is about process of various economical indicators and political news as factors of rate prediction. The prediction is about forecast process of dealers. The strategy making is about decision of how much dealers order to buy or sell currencies.

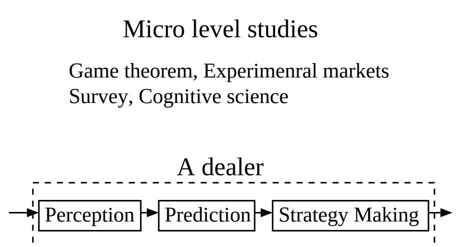


Figure 2.4: Steps of dealers' process

Although these micro level studies reveal some important features of dealers' learning, they have some problems. First, some micro-level studies neither propose nor describe linkage between behavior pattern at the micro level and input-output relation at the macro level. Second, even if some micro level studies such as game-theoretic studies try to provide the linkage, their models can not explain many interesting phenomena in the real market because they assume dealers' rationality like REH models.

The micro level studies include game theoretic models, survey studies, cognitive science studies, and experimental markets. First, we briefly review the results of field work studies (survey studies and cognitive science studies) of the real markets in section 2.3.1. Second, we explain game theoretic models and experimental markets, and show their problems in section 2.3.2.

2.3.1 Fieldwork

The field work studies try to reveal many features of dealers' perception and prediction process in markets empirically. To do so, they survey dealers' forecasts or interview with dealers. They then analyze these field data with categorization or statistics.

These studies have found the following features of dealers:

First, based on survey data, some studies show that actual dealers use different method of the expectation formation among different forecast terms [47, 51, 68, 71, 113]. In short, the result of these studies is that expectations over short horizons are not consistent with that over long horizons: the expectations over short horizons tend to incorporate band wagon effects and that over long horizon display regression property.

Second, it is found that forecasts of market participants are heterogeneous [68]. That is, mechanisms of expectation formation are significantly different among market participants. The mechanisms reflect individual experiences or appreciation.

Third, some studies show that forecasts of actual dealers are affected by other dealers' orders or forecasts [57, 81, 82]. They usually try to acquire new information from other dealers' orders in order to know other dealers' forecasts.

Finally, some studies reveal a part of mechanism of how actual dealers use knowledge about past forecasts or past cases [57, 109]. For example, the actual dealers usually grasp the gist of news headline, and make it the standard for comparison for that headline the next time it is encountered.

Although these studies reveal these important features of agents' learning, they however neither propose nor describe linkage between such features at the agent level and rate dynamics at the market level.

2.3.2 Game Theoretic Models and Experimental Markets

Game theoretic studies model a exchange market as a game of incomplete or complete information [15, 80, 85, 87, 96, 100]. Experimental markets studies verify the results of the game theoretic studies using laboratory data from small-scale markets [33, 76, 110, 111]. In their models, each dealer knows information about reservation value of his own capital, but does not know other dealers' preferences, neither strategies. Using past data of other dealers' order (bids and asks), each dealer infers other dealers' preferences and strategies, and finally determines his own order. That is, these studies mainly deal with the strategy making process of dealers.

From a viewpoint of analysis of the real rate dynamics, these studies have problems. First, their approach relies heavily on prior common-knowledge assumptions: each dealer must have prior knowledge about types of other dealers' preferences and strategies and/or other dealers' rationality. Like REH, these assumptions are incredible and unrealistic in the real markets. Second, they don't refer to dealers' mental models of the economic structure of the market. In the game theoretic models and experimental markets, dealers infer their own final valuations using only past orders. Namely, they don't infer economic structures relevant to the rate determination using data about economic fundamentals. Their results have nothing to do with the results of the filedwork about the perception and prediction process. So, their results can't explain rate dynamics in the real markets well.

2.4 Multiagent models: Integration of Micro and Macro

In order to establish linkage between micro and macro, several alternative approaches are proposed. Among these, there is an *multiagent models* approach [4, 36, 64, 86, 98, 104]. Previous studies in this approach make market models with artificial adaptive agents and conduct computer simulations (fig. 2.5). Then the studies analyze the dynamics of the market model and use the results of the analysis to understand the actual markets.

This approach is inspired the artificial life studies and artificial society studies. These studies try to integrate the micro and macro levels. They regard that many phenomena and patterns at the macro level emerge as a result of interaction between simple rules at the micro level. That is, they try

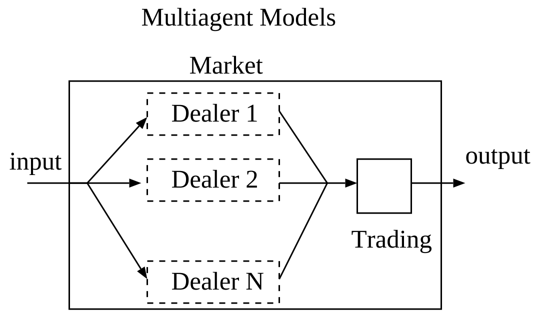


Figure 2.5: Framework of multiagent models

to explain the relation between micro and macro levels with self-organization theory.

The meaning of "to explain" in artificial life studies and artificial society studies is slightly different from that in other fields. Their aim is to provide initial microspecifications (initial agents, environments, and rules) that are sufficient to "generate" the macrostructures of interest. They consider a given macrostructure to be "explained" by a given microspecification when the latter's generative sufficiency has been established.

The multiagent models follow their principals. The micro components of the model is decision rules of dealers, and the macrostructure of interest is the rate dynamics. Interaction between micro components is interaction of learning or strategies. The aim of multiagent models is to generate the rate dynamics from the interaction between micro components.

However, there are two problems in the previous multiagent models for analysis of the actual market.

First, while the previous multiagent models mainly deal with the adaptation of the strategy making process like game theoretic studies, they ignore the prediction process. That is, the agents are described as rules which represent mere relationship between stimulus (information) and response (order). The rules don't represent expectation formation or risk management. Hence, the agents don't have mental models (internal representation) of economic structure. In fact, the development of actual dealers' mental models is corresponded to the adaptation of the prediction process rather than strategy making process. Hence they have nothing to do with the results of the fieldwork about the perception and prediction process.

Second, the previous studies use only trend factors. They don't use the actual data series about economic fundamentals and political news because the agents don't take account economic structures. Therefore, they can't investigate the actual rate dynamics quantitatively.

In order to overcome these problems, we propose a new approach of foreign exchange market studies, an *artificial market approach*. The artificial market approach integrates the fieldwork and multiagent models in order to explain the micro and macro relation in markets. In the next chapter, we show the framework of the artificial market approach.

Chapter 3

Framework of the Artificial Market Approach

In this chapter, we would like to explain the framework of the proposed approach, the *artificial market approach*.

The artificial market approach is an integration of the fieldwork and the multiagent models. In this approach, the field data which are acquired in the filedwork were used in both construction and evaluation of a multiagent model.

3.1 Outline of Procedure

The artificial market approach is divided into the following three steps (fig. 3.1):

1. **Observation in the field:** field data of actual dealers' behavior are gather by interviews and questionnaires. Then, the learning and interaction patterns of the dealers are investigated. Especially, we try to

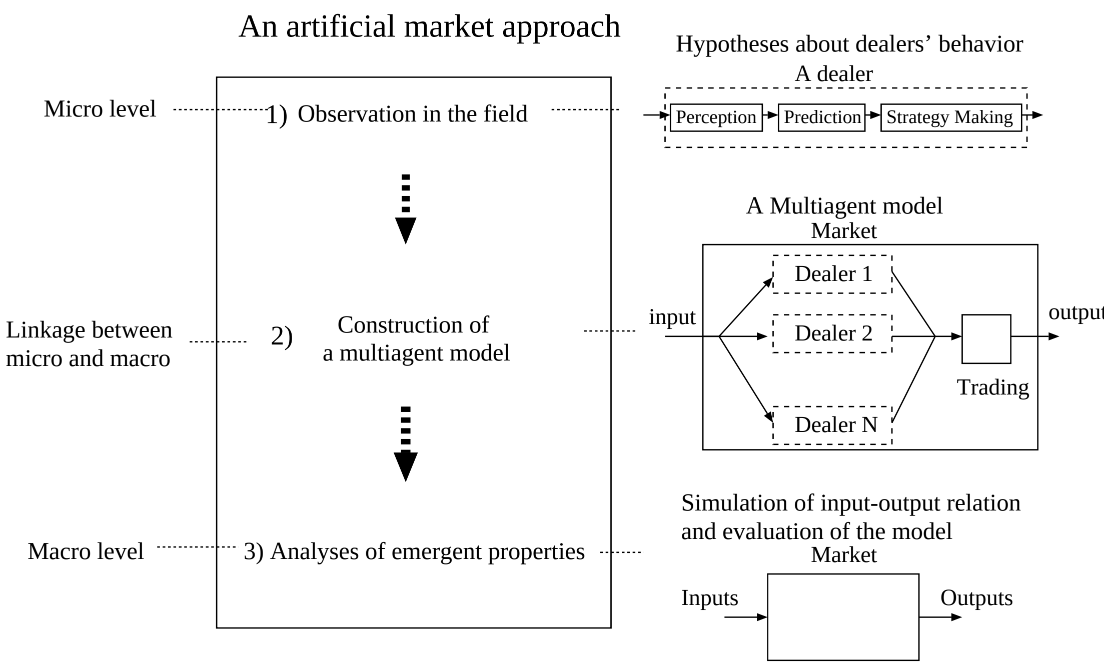


Figure 3.1: Framework of the artificial market approach

know the following things:

- What kinds of decision rules, forecast rules, and learning rules the dealers have?
- What information make the dealers change their rules?
- How do the dealers change their rules?
- How do the dealers communicate with others in their learning?

As a result of analysis of these field data, we proposed some hypotheses about dealers' behavior pattern: decision rules, learning rules, and interaction pattern.

2. **Construction of a multiagent model:** a multiagent model of the market is implemented based on the hypotheses. The minimal com-

ponent of the model is each rule which agents have. Each rule may change or interact with other rules the way the hypotheses describe. As a result of the dynamics of rules, the model simulate rate dynamics at the macro level. Hence, the model provides linkage between the simple rules of agents at the micro level and the complex pattern of rate dynamics at the macro level.

3. **Analysis of emergent phenomena :** in order to evaluate the model, the simulation results of the model are analyzed. We conduct simulation using actual data of economic fundamentals in the real world. Based on the simulation results, we verify whether the model can explain emergent phenomena of the actual market in the following points: whether the rate dynamics produced by the model fit with that in the real world, whether the dealers' behavior patterns observed in the model fit with those in the field data, and whether the dealers' behavior patterns can explain the rate dynamics.

3.2 Advantages of the Approach

The artificial market approach has the following advantages over previous studies:

- This approach provides **the linkage between micro and macro**. That is, it explains how the micro behavior and interaction of agents cause emergent phenomena at the macro level.

- A multiagent model in this approach **reflects the results of the fieldwork in the real world data**, while the previous multiagent models have nothing to the field data. First, the model is constructed on the basis of the observation of dealers' behavior. Next, in order to investigate emergent properties in the real markets, actual data about economic fundamentals and news are used in the simulation.

- The model is **evaluated at both micro and macro levels.** in this approach.
  - At the micro level, the behavior patterns of agents in the model are compared with those of actual dealers in the field data.
  - At the macro level, it is verified whether the model can simulate emergent phenomena of rate dynamics in the real world.

These advantages of the artificial market approach are necessary for **quantitative analysis of the micro-macro relation** in the actual markets.

The details of the approach are described in the following three chapters. In chapter 4, observation in the field and it results are shown. In chapter 5, we explain the framework of the multiagent model. In chapter 6, the simulation results are illustrated.

Chapter 4

Hypotheses about Dealers' Behavior

In this chapter we would observed the actual dealers' behavior by using interviews and questionnaires. Based on these field data, we propose a hypothesis of dealers' learning. This hypothesis is also used in the construction of a multiagent model as a rule of agents' interaction and learning.

First, we explain the aim and methods of the observation of the actual dealers' learning. Second, the results of interviews with actual dealers are shown. Third, the results of the questionnaires are described. Finally, we discuss the features of dealers' learning in markets based on the results of the interviews and the questionnaires.

4.1 Observation at the Micro Level

In order to investigate actual dealers' behavior, we carried out both interviews and questionnaires with actual dealers. The aims of these two methods are different. The interviews provide time series data of temporal change of dealers' rules, while the questionnaires provide snapshot data of distributed patterns of dealers' rules (fig. 4.1).

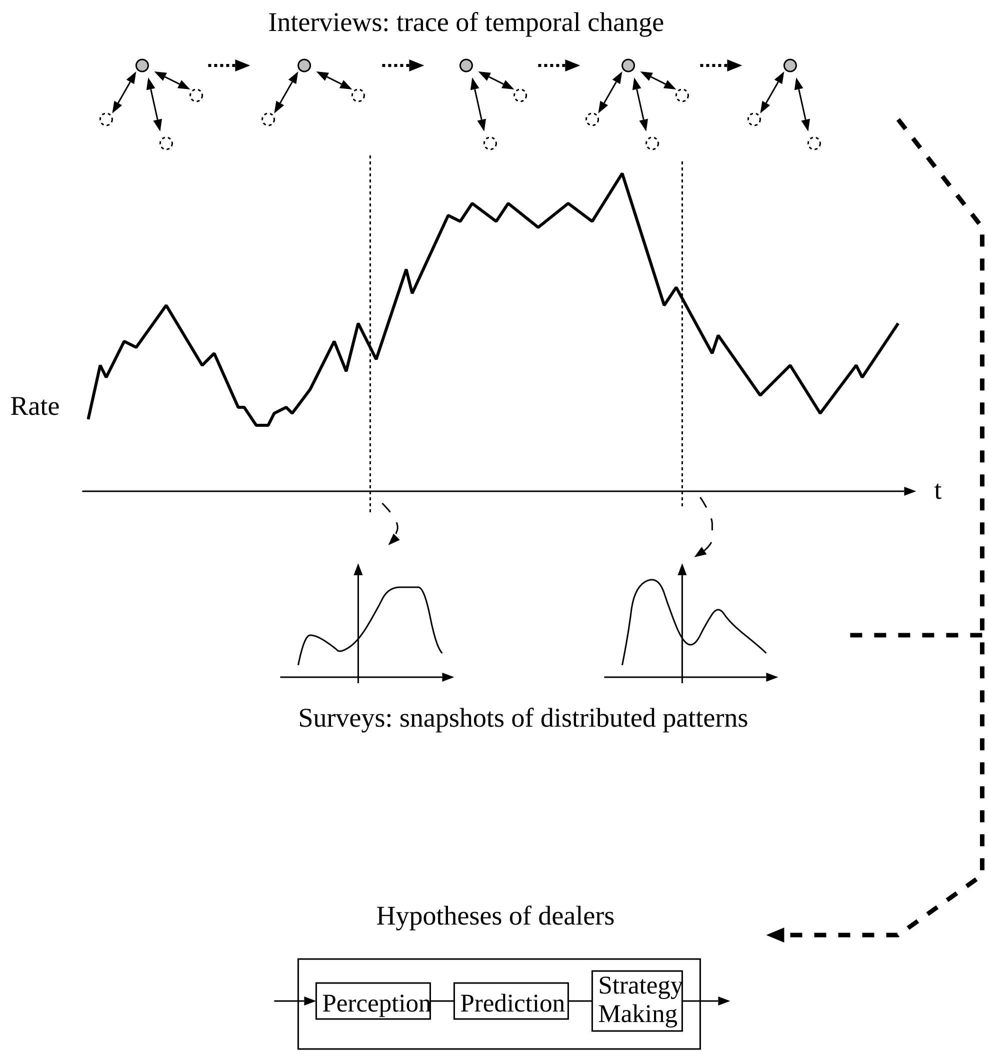


Figure 4.1: Overview of observation at the micro level

The main purpose of the interviews is to trace the temporal change of the dealers' learning and decision making process. Especially, from the interview data, we want to know the following things:

- What kinds of decision rules, forecast rules, and learning rules the dealers have?
- What information make the dealers change their rules?
- When do the dealers change their rules?
- How do the dealers change their rules?
- How do the dealers communicate with others in their learning?

On the other hand, the main purpose of the questionnaires is to know the distributed patterns of the dealers' rules in the market at each period. By the questionnaires, we want to know the following things:

- How are the rules distributed at each period?
- How do the rules change their frequencies in the market?
- What differences of learning rules exist among dealers?

Considering both temporal changes and distributed patterns of dealers' opinions, we propose a hypothesis about dealers' learning.

4.2 Interviews: Trace of Temporal Change

We held interviews with two dealers who usually engaged in yen-dollar exchange transactions in Tokyo foreign exchange market. The first dealer (X) was a chief dealer in a bank. The second dealer (Y) was an interbank dealer in the same bank. They had more than two years of experience on the trading desk.

4.2.1 Interview Methods

The interviewees were asked to explain the rate dynamics of the two years from January 1994 to November 1995, when the interview took place. Concretely, we asked each dealer to do the following things:

1. To explain freely (i.e. without referring to any material) the rate dynamics of these two years and also to talk both about how he forecasted the weekly yen-dollar rates and about how he recognized the market situations such as the rate trend.

2. To divide these two years into several periods according to his recognition of the market situations, to talk about which factors he regarded as important in his rate forecasts in each period, to rank the factors in order of weights (importance), and to explain the reason for his ranking. When he changed the ranking between periods, to tell the reasons for the reconsideration in detail.

4.2.2 Results: Features of Learning

The division of the two years and the ranking of factors are shown in table 4.1 and 4.2.

From the interview data of the two dealers, we found that the learning of prediction methods (the weights of factors) in the market has the following features:

- The prediction methods are **continuously changing from one period to another**. This is contrary to the assumption of the REH, according to which the prediction methods must be consistent throughout all periods. For example, in table 4.1 and 4.2, the trade balance

1994

	I Jan	II Feb-Jun	III Jul-Oct	IV Nov-Dec
Actual	→	↘	→	→
Forecast	→	↘	→	→
Factors ranking	1.Mark 2.Season- al factor	1.**Chart** 2.**Trade** 3.Politics	1.**Chart** 2.Deviation 3.Politics	1.Season- al factor

1995

<table>
<tr><th>V
Jan</th><th>VI
Feb-Apr</th><th>VII
May-Jul</th><th>VIII
Aug-Sep</th><th>IX
Oct-Dec</th></tr>
<tr><td>↗</td><td>↘</td><td colspan="2">↗</td><td>→</td></tr>
<tr><td>↗</td><td colspan="2">↘</td><td>↗</td><td>→</td></tr>
<tr><td>1.Season-
al factor</td><td colspan="2">1.Trade
2.Politics
3.Mexico
4.Chart</td><td>1.Deviation
2.Intervention</td><td></td></tr>
</table>

The forecast factors are ranked in order of importance. Because the boldfaced factors are common to both dealers, they are considered as market consensus of each period.

Table 4.1: Results of interview with dealer X.

1994

	I Jan-May	II Jun	III Jul-Dec
Actual	↘	↘	→
Forecast	↘	→	→
Factors ranking	1. **Trade** 1. Order 3. **Chart**	1. Rate level	1. Order 2. **Chart**

1995

IV Jan-Feb	V Mar-Apr	VI May-Jul	VII Aug-Dec
↘	↘	→	↗
↘	↘	→	↗
1. **Politics** 2. Mark 2. Announcement	1. **Politics** 1. Order 1. Intervention	1. **Chart** 2. Order	1. **Intervention** 2. Politics

The forecast factors are ranked in order of importance. Because the boldfaced factors are common to both dealers, they are considered as market consensus of each period.

Table 4.2: Results of interview with dealer Y.

factor was regarded as important only in the period II, VI, and VII by the dealer X and the period I by the dealer Y, although there are always the large trade surplus of Japan throughout these two years. Namely, there are fashions of interpretation of factors in markets. The dealers called such fashions as *market consensus*. The dealer X said that dealers often ignored the data or factors which are against market consensus.

- When each dealer changes his prediction method, he **communicates with other agents** in order to get information about which factors are regarded important by many agents, and **replace (a part of) his prediction method with other agent's one which can explain better the recent rate dynamics**. Both dealers said that they frequently told with other dealers and read news letters or economical reports especially when the trend were changing. With such communication, they tried to infer new market consensus.

- **When each dealers forecast was quite different from the actual rate, he recognized that he needs to change his weights**. For example, at the end of the period VII of the dealer X, he thought that the chart trend was still sideway. However the market trend already changed to the quick yen up trend since May 1995. When the rate reached the level of 92 yen, he suddenly recognized that the trend changed. Then he discarded his old opinions about factors and adopted new opinions. That is, large deviation between his forecasts and actual rates promoted change of his opinions.

4.2.3 Hypothesis

From the features of dealers' learning which have been said in section 4.2.2, we proposed the following hypothesis at the micro level in markets:

> *When the forecasts based on his opinion are largely different from the actual rates, each dealer replace (a part of) his opinions about factors with other dealers' successful opinion.*

In the next section, this hypothesis is verified with the questionnaire data of dealers' opinions about factors.

4.3 Questionnaires: Snapshots of Distributed Patterns

If the above hypothesis is true, the frequency of successful weights in a market must be larger after the trend changed. Then, *the market average of data weights must shift to the value of successful weights.* In order to verify this proposition, we took a questionnaire for dealers in March 1997.

4.3.1 Methods

The questionnaires are undertaken in March 1997 and July 1997. In March 1997, the market trends changed from the upward trend to the downward trend for dollar. In July 1997, it changed from the downward trend to the upward trend for dollar. All answerers are dealers who usually deal with exchange transactions in a bank. The questionnaires are shown in appendix B.

The answerers were asked questions about the following matters:

1. Importance of 25 factors in the recent trend[1].
2. Importance of 25 factors in the previous trend[2].
3. Forecasts which each dealer made before the trend changed.

The 25 factors are economic activities, price, short-term interests, money supply, trade balance, employment, personal consumption, intervention, mark-dollar rates, commodities, stock, bonds, chart trends (1 week), chart trends (over 1 month), attitude of band of Japan, attitude of FRB, attitude of export and import firms, attitude of insurance firms, attitude of securities firms, attitude of other banks, attitude of foreign investors, the other factor.

4.3.2 Results: verification of hypothesis

If the hypothesis in section 4.2.3 is true, the corollary follows:

> *Successful opinions with more accurate forecasts spread in the market.*

This corollary implies that the market averages of each factor's weights change toward the averages which are weighted with forecast accuracy of the factor's weights. As mentioned in section 4.2.2, the interview data suggest that the factors' weights which can forecast more accurately have lager frequency after dealers change their opinions. Hence, the market averages of each factors' weights change to the averages which are weighted with their forecast accuracy.

[1] The recent trend is the downward trend of dollar in the first questionnaire, the upward trend of dollar in the second questionnaire.

[2] The previous trend is the upward trend of dollar in the first questionnaire , the downward trend of dollar in the second questionnaire.

The forecasts accuracy must reflects how factors' weights forecast close to the actual rate. The forecast accuracy of dealer i is defined using a product of -1 and an absolute value of a difference between his predicted rate and the actual rate:

$$F^i = \max_{j \in all\ dealers} [|\tilde{R}^j - R|] - |\tilde{R}^i - R|, \tag{4.1}$$

where, F^i is a forecast accuracy of a dealer i, $\tilde{R}^j$ is a forecast value of a dealer j and R is an actual rate. The first term in equation 4.1 is necessary because the forecast accuracy must be in inversely proportion to the difference.

The average of each factor which is weighted with the forecast accuracy is calculated as follows:

$$\text{Weighted average} = \sum_{i \in all\ dealers} W^i \times \frac{F^i + 1}{\sum_{j \in all\ dealers} (F^j + 1)}, \tag{4.2}$$

where, W^i is the factor's weight of dealer i. Forecast accuracy is added one so that all weights which can have non zero contribution to the weighted average.

Using the questionnaire data, we tested the corollary. To do so, first we calculated the market averages of each factor's weights before the change of trend, those after the change of trend, and the weighted average in the equation 4.2, which used weights before the change. Second we calculated differences between market averages of weights before the trend change and those after the trend change. We also calculated differences between market averages of weights before the trend change and the weighted average before the trend change. Finally, correlation coefficients between these two differences are calculated. If the corollary is true, the market average after the trend change must be nearer the weighted average. Hence, the two differences must have positive correlation.

As a result, there were positive correlations between the two differences both in the first questionnaire and in the second questionnaire (table 4.3). Namely, successful opinions which can forecast more accurately, are considered to spread in the market.

	The first questionnaire	The second questionnaire
Number of samples	25	25
Correlation	0.284	0.176
Probability	$P < 0.1$	not significant

Table 4.3: Correlation between differences

In summary, the hypothesis implies that the learning pattern of actual dealers is similar to the adaptation in ecosystem. In our multiagent model, the adaptation of agents in the market will be described with genetic algorithm, which based on ideas of population genetics.

4.4 Discussion: Ecology of Dealers' Beliefs

In this section, we discuss the features of dealers' learning in markets, based on the results of the interviews and the questionnaires. The discussion mainly deal with the analogy between population dynamics in biology and dynamics of dealers' opinions. We also provide base of the construction of the multiagent model which is described in chapter 5.

By nature, foreign exchange markets have following features:

1. Each agent's payoff depends not only on his own behavior, but also on other agents' decisions.

2. The number of agents is too large to make them all know the other agents' methods of decision making. Thus especially the assumption of REH "All agents know that all agents are the same in the Perception, Prediction, and Strategy Making step. Moreover, all agents know that all agents know it." is difficult to be satisfied.

3. The foreign exchange market has many levels: overall system level, agent level, and belief system level and so on. Units at one level are aggregated to units at the next higher level. Hence, there is a micro and macro problem.

Because of these features, foreign exchange markets are complex. In other words, they are not linear, static, statistically predictable systems as many REH models assume. Therefore, agents must build up his own mental models of markets and use them in order to make prediction. There is no "grand theory" for prediction in a foreign exchange market. Hence, each agent always tries to understand patterns of the rate change by making his own scenario. In other words, he tries to find causal relations between factor change and rate change from past data and behavior of other agents.

The field data and many books show that prediction of actual dealers in the foreign exchange market is actually like the following [60, 114, 115, 121].

1. Prediction in the market is that of "ways of others' prediction". Therefore, other agents' judgments, opinions, and behavior are very important information for decision making in a market. Actually, all dealers in the market communicate with other dealers in order to get information about other dealers' decision and prediction. That is, **agents strongly interact with each other in prediction**.

2. Importance of factors which are used in prediction always change: at some periods, money supply was regarded as important, but at other periods balance of trade was. Causal relations between factors and rates can also change: a factor which was once regarded to cause yen appreciation may be cause of yen depreciation today. Therefore, **each agent tries to find market consensus**, kinds of factors which are *now* regarded as important by many agents in the market and to coincide his considered factors with them in order to improve his prediction.

From the above description, it is understood that each agent builds up his belief system of the market, where building blocks are beliefs about factors, and that each agent improves his belief system by communicating with other agents. In REH models, building blocks are fixed rational agents. The REH models do not explain how agents learn his rationality: the rationality is given and unchanged. If exchange rate models which are built up from the agent level have the above problems, why not build up a model from a lower level such as the belief system level?

Let us consider beliefs about factors as building blocks of an exchange rate model. Beliefs about factors have several important features. First, they are replicators: they are imitated or transmitted by other agents with some degree of reproductive accuracy. Second, they are instructors: they organize each agent's belief system about the foreign exchange market, and according to his own belief system each agent makes prediction and decides behavior. Third, they are under selective pressure: each agent always replaces his beliefs with new beliefs that are plausible, in order to improve his prediction. At last, they have sustained variation: each agent generates new belief system by communicating with other agents or by himself.

From the viewpoint of these features, beliefs about factors are seen to be analogous to biological genes. Biological genes organize each individual's chromosome. Chromosomes are changed by crossover[3] and mutation. And chromosomes with lower fitness[4] are replaced with those with higher fitness. That is, selection works with chromosomes. Analogy between population genetics and foreign exchange markets is described in Table 4.4.

Genetics	Market
a gene	a belief about a factor
a chromosome	a belief system
selection	imitation of successful belief systems
crossover	recombination of beliefs by communicating with other agents
mutation	generation of new belief system by himself
fitness	precision of prediction

Table 4.4: Analogy between genetics and a market

Dawkins calls conceptions which are units of cultural transmission and imitation as *memes* [35]. Beliefs about factors are thought of one example of memes.

From the above description, we can get the following conclusion. Each agent behaves based on his own belief system and the behavior of agents change the environment, the exchange rate. The belief system of each agent changes in time influenced by other agents' belief systems. This procedure is like adaptation in ecosystem. In this study, adaptation in the market is described with genetic algorithm, which is based on ideas of population genetics.

[3]Crossover is recombination of chromosomes, where the parts of two chromosomes are exchanged

[4]Fitness is an index of how good a chromosome is. In biology, fitness is ability to reproduce and to survive

In the next chapter, we explain the framework of the proposed multiagent model.

Chapter 5

Construction of a Multiagent Model

In this chapter we propose a multiagent model of a foreign exchange market, based on the field data in chapter 4.

We focus on similarities of the interactions between agents in learning to the GA operations, as mentioned in section 4.4, and describe the interaction based on GAs in our model.

In section 5.1, the framework of the model is described. In section 5.2, the flow of the algorithm of the model is explained using an example.

5.1 Framework of the Model

The multiagent model of a foreign exchange market in this study is named

A GEnetic-algorithmic, **D**ouble **A**uction market **SI**mulation
in **TO**kyo **F**oreign exchange market.
(**AGEDASI TOF**)

Using weekly data in Tokyo foreign exchange market, AGEDASI TOF iteratively executes the following five steps: Perception, Prediction, Strategy Making, Rate Determination, and Adaptation Step (Fig.5.1).

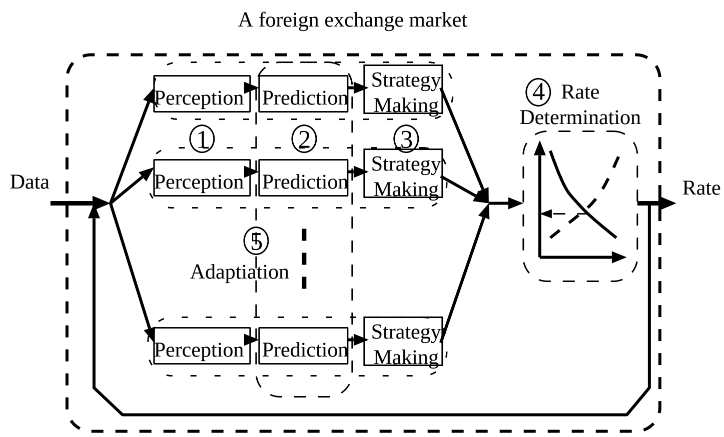


Figure 5.1: Framework of model.

At 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 the following three steps:

Perception: Each agent interprets changes of various raw data such as economical 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: Using their own percepted factors, each agent predicts future economical situations and future changes of exchange rates from the current rates.

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

As a consequence of this decision making process, 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: As explained in section 2.2.1, exchange rates are decided to the equilibrium rates where supply and demand meet. That is, the equilibrium rate is the market clearing rate.

Adaptation: After the rate determination, each agent improves his prediction method using other agents' prediction. The proposed model uses GAs to describe the interaction between agents in learning.

A set of these five steps is called a *generation*. One generation corresponds to one week in the real market. Each week starts at the perception step and ends at the adaptation step (fig. 5.2). There is one trading in each week. Each dealer is given weekly data before the trading (Step 1). The data are economic indices and news immediately after the rate determination of the **T-1**th week just before that of the **T**th week. Each dealer predicts the market clearing rate in the **T**th week just before trading (Step 2). He tries to make optimal position in trading (Step 3). As a result of trading, the market clearing rate of the **T**th week is determined (Step 4). He learns from others comparing their predictions to the market clearing rate (Step 5).

5.1.1 Step 1: Perception

Each agent first interprets raw data and perceives news about factors affecting the yen-dollar rate. We assume that all agents interpret raw data in the

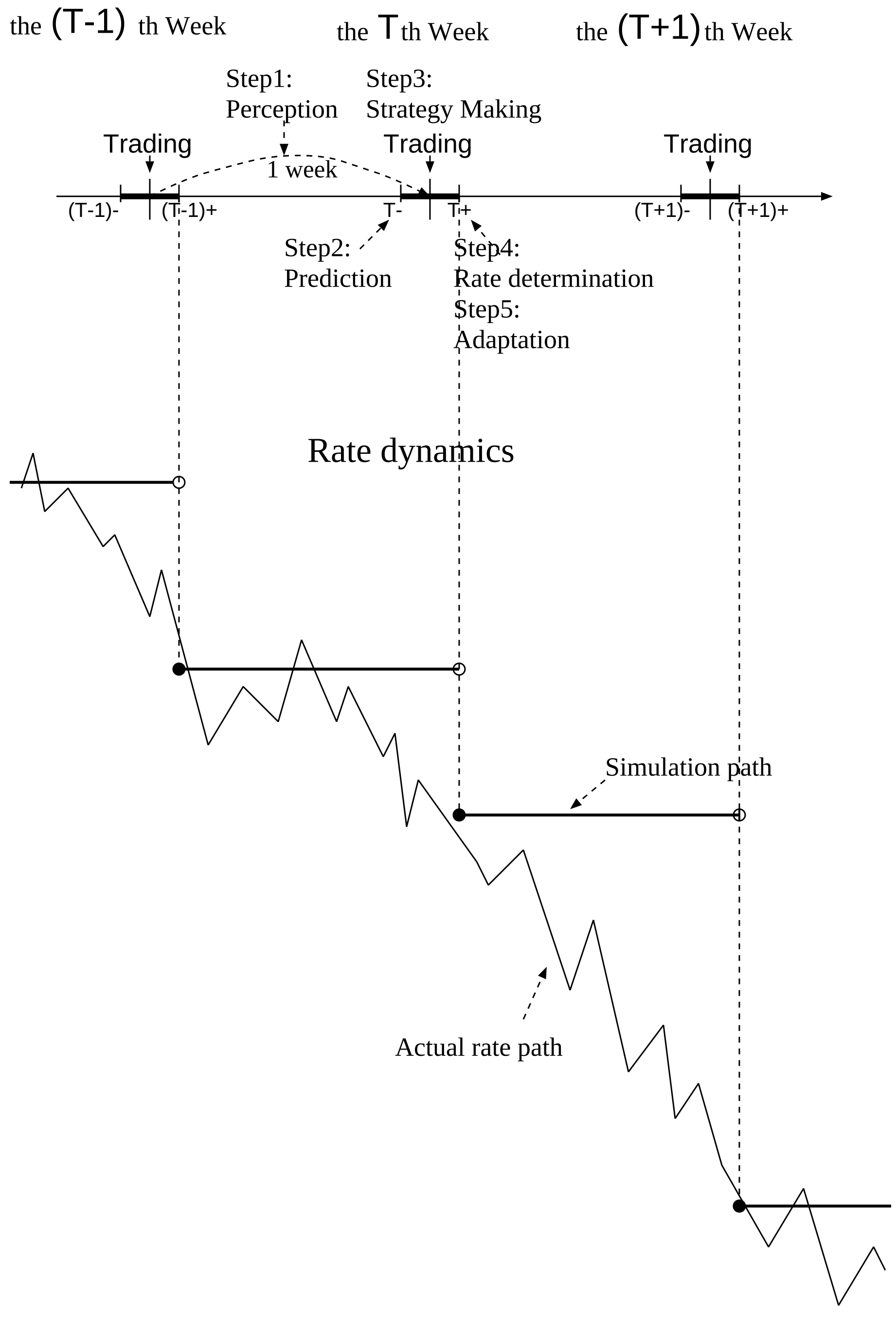


Figure 5.2: Time structure of AGEDASI TOF.

same way.

$x_{i,t}$ is defined as data which are made by interpreting raw data **i** between the end of week **t-1** and the beginning of week **t**. In the present study, it is assumed that all agents interpret raw data in the same way. Thus the results of interpretation, the data $x_{i,t}$'s, are the same for all agents.

The data $x_{i,t}$ are made by weekly change of 17 raw data (Tab.5.1). Those values range discretely from -3 to $+3$. Plus values indicate that the data change causes dollar depreciation according to the traditional economic theories. Minus values indicate dollar appreciation. For an instance, a comment "Unemployment Rate of United States decreased largely" is coded as "Employment : -3". And data "Last week, the yen/dollar rate decreased beyond expectation" is coded as "Change in the last week : $+2$".

External data are defined as the data of economic fundamentals or political news (No.1-14 in table 5.1), because they are data of the events in the real world. *Internal data* are defined as data of shot-term or long-term trends of the chart (No.15-17 in table 5.1), because they are calculated using the rate which the model made in the simulation.

5.1.2 Step 2: Prediction

After perception, using above data, each agent predicts future change of the rate.

Each agent has his own weights of the 17 data. $w^j_{i,t}$ is defined as a weight of each datum **i** in each agent **j**'s prediction of the future rate at week **t**. The value of $w^j_{i,t}$ ranges among nine discrete 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

	Data ($x_{i,t}$)	Raw Data
1	Economic activities	[U][J] GDP,NAPM index etc.
2	Price	[U][J] Price index
3	Interest rates	[U][J] Official rate
4	Money supply	[U][J] Money supply
5	Trade balance	[U][J] balance of trade
6	Employment	[U] Unemployment rate
7	Personal consumption	[U] Retail sales
8	Intervention	[U][J] Intervention
9	Announcement	[U][J] Announcement of VIP
10	Mark	the dollar-mark, yen-mark rate
11	Oil	Oil price
12	Politics	Political condition
13	Stock	[U][J] Stock price
14	Bond	[U][J] Bond price
15	Short-term Trend 1	Change in the last week
16	Short-term Trend 2	Change of short-term trend 1
17	Long-term Trend	Change through five weeks

([U]=USA, [J]=JAPAN.)

Table 5.1: Input data.

week **t**. It is assumed that each agent **j** predicts ΔS_t based on the summation of products of the data $x_{i,t}$ and the weights $w^j_{i,t}$. By substituting this summation into a truncation function, each agent makes the prediction value $\mathbf{E}^j_t[\Delta S_t]$. This is represented as follows:

$$\mathbf{E}^j_t[\Delta S_t] \equiv \text{trunc}\left(\sum_{i=1}^{n} w^j_{i,t} x_{i,t}\right), \tag{5.1}$$

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

$$\mathbf{Var}^j_t[\Delta S_t] \equiv \left(\sqrt{|(wx_+)^2 - (wx_-)^2|}\right)^{-1}, \tag{5.2}$$

where wx_+ denotes the summation of $w^j_{i,t} x_{i,t} > 0$ and wx_- the summation of $w^j_{i,t} x_{i,t} < 0$. The wx_+ means the summation of effects of dollar depreciation factors and the wx_- means the summation of effects of dollar appreciation factors. Because the variance is inversely proportional to the difference between the wx_+'s size and the wx_-'s size, it means the distribution of factors of two sides. When an agent has only one sided factors, the variance of his forecast is very small. When he has factors of both side, the variance of his forecast gets large.Thus, the variance is inversely proportional to the degree of confidence of each agent's forecast.

It must be noted that $\mathbf{E}_t^j[\Delta S_t]$ and $\mathbf{Var}_t^j[\Delta S_t]$ are different for both each agent **j** and each week **t** because the weights are different.

5.1.3 Step 3: Strategy Making

Each agent has dollar assets and yen assets. Each agent decides, on the bases of his own prediction, his trading strategy (order to buy or sell dollar) . He maximizes his utility function of his expected return of the next week. The strategy making process of the proposed model is common to the conventional portfolio balance model in econometrics.

Let us define the following variables about an agent **j**.

q_t^j**:** The amount of dollar assets of the agent **j** at this week **t** in terms of dollar (not determined).

W_t^j**:** The amount of whole assets (the dollar and yen assets) of the agent **j** at this week **t** in terms of yen.

$\tilde{S}_{t+1}^j \equiv \Delta S_t + S_t$**:** Agent **j**'s forecast of logarithm of yen-dollar exchange rate at the next week **t+1**.

S_t**:** Logarithm of yen-dollar exchange rate at this week **t**. (not determined).

The expected return in terms of yen ($\tilde{R}_t^j$) is calculated as follows.

$$\begin{aligned}\tilde{R}_t^j &= \frac{\{\exp(\tilde{S}_{t+1}^j) - \exp(S_t)\}}{\exp(S_t)} q_t^j \\ &= \{\exp(\Delta S_t) - 1\} q_t^j \\ &\approx \Delta S_t q_t^j.\end{aligned} \tag{5.3}$$

In AGEDASI TOF, utilities of all agents are assumed to be the same.

$$U(\tilde{R}_t^j) \equiv -\exp(-a\tilde{R}_t^j),$$

where $a > 0$ denotes risk aversion in economics. When $\tilde{R}_t^j$ has the normal distribution N($E[\tilde{R}_t^j]$, $Var[\tilde{R}_t^j]$), the logarithm of the expected utility is as follows[1].

$$ln(E[U(\tilde{R}_t^j)]) = E[\tilde{R}_t^j] - \frac{1}{2} a Var[\tilde{R}_t^j]. \tag{5.4}$$

Substituting the equation 5.3 into the equation 5.4, the logarithm of the expected utility is calculated as follows.

$$ln(E[U(\tilde{R}_t^j)]) = E_t^j[\Delta S_t] q_t^j - \frac{1}{2} a Var_t^j[\Delta S_t](q_t^j)^2 \tag{5.5}$$

Each agent is assumed to divide his whole assets between dollar assets and yen assets with the optimal ratio which maximizes the equation 5.5. The optimal quantity of his dollar assets q_t^{j*} is as follows:

$$q_t^{j*} = \frac{1}{a} \frac{\mathbf{E}_t^j[\Delta S_t]}{\mathbf{Var}_t^j[\Delta S_t]}. \tag{5.6}$$

[1]This calculation result is got by Taylor extension.

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:

$$\text{Order quantity } \Delta q_t^{j*} \equiv q_t^{j*} - q_{t-1}^j. \tag{5.7}$$

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

$$\text{Order rate} \equiv \mathbf{E}_t^j[\Delta S_t]. \tag{5.8}$$

5.1.4 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 quantity of demand and that of supply are equal. The rate in this week is the equilibrium rate.

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

$$\mathbf{DD}_t(x) = \sum_{j \in J_x^D} \Delta q_t^{j*}, \tag{5.9}$$

$$\left(J_x^D \equiv \{ j : \ \Delta q_t^{j*} > 0 \text{ and } \mathbf{E}_t^j[\Delta S_t] \geq x \} \right).$$

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:

$$\mathbf{SS}_t(x) = -\sum_{j \in J_x^S} \Delta q_t^{j*}, \tag{5.10}$$

$$\left(J_x^S \equiv \{ j : \ \Delta q_t^{j*} < 0 \text{ and } \mathbf{E}_t^j[\Delta S_t] \leq x \} \right).$$

As explained in subsection 2.2.1, the exchange rate of the market is decided to the equilibrium rate, where quantity of demand and that of supply are equal:

$$S_t = S_{t-1} + x^*, \tag{5.11}$$

$$\left(\mathbf{DD}_t(x^*) = \mathbf{SS}_t(x^*) \right).$$

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

$$q_t^j = \begin{cases} q_t^{j*} & \text{if } j \in J_{x^*}^S \text{ or } J_{x^*}^D \\ q_{t-1}^j & \text{otherwise} \end{cases} \tag{5.12}$$

5.1.5 Step 5: Adaptation

In the proposed model, different agents have different prediction methods (combinations of the weights $w_{i,t}^j$). After the rate determination, each agent improves his prediction method using other agents' prediction. The model uses genetic algorithms to describe the interaction between agents in learning.

Because the weights are also different for each week **t**, it is very important how they change in time. Each agent is assumed to change his way of prediction in order to improve prediction. That is, the change of the weights is a result of the adaptation of each agent. To describe this adaptation, AGEDASI TOF applies genetic algorithm.

As shown by its name, the fundamental ideas of genetic algorithm come from population genetics. In genetic algorithm, the frequencies of the chromosomes in a population and the values of the chromosomes are changed with three operations; selection, crossover, and mutation. With selection, each chromosome in the population can reproduce its copies at a possibility proportionate to its fitness. Then a frequency of a chromosome with high fitness value increases and a frequency of a chromosome with low fitness value decreases in the next generation. Crossover operator generates new chromosomes by recombining the pair of the existing chromosomes. Mutation operator generates new ones by randomly changing the value of a position within chromosomes.

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

$$w_{i,t}^j = \begin{pmatrix} +3 & +1 & +0.5 & +0.1 & 0 & -0.1 & -0.5 & -1 & -3 \\ \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow \\ \mathbf{A} & \mathbf{B} & \mathbf{C} & \mathbf{D} & \mathbf{E} & \mathbf{F} & \mathbf{G} & \mathbf{H} & \mathbf{I} \end{pmatrix} \tag{5.13}$$

A chromosome represents a string of all weights of one agent, that is his prediction method:

$$\text{Chromosome } \mathbf{w}_t^j = (w_{1,t}^j, w_{2,t}^j, \cdots, w_{n,t}^j). \tag{5.14}$$

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 foreign exchange market.

The model is based on Goldberg's simple GA [56]. The detailed description of the simple GA is shown in appendix A. Selection operator, one of GA operators, replace some chromosomes with others which have higher fitness values. This percentage of selection is called a *generation gap*, G.

In this model, the fitness value of each chromosome is calculated using the difference between its forecast mean and this week's rate as the equation. Hence, the more precisely a chromosome predicts the rate, the higher its fitness value. Concretely, the fitness of a chromosome is a product of -1 and an absolute value of a difference between the predicted rate change $\mathbf{E}_t^j[\Delta S_t]$ and the actual rate change ΔS_t:

$$\begin{aligned} \text{fitness of } \mathbf{w}_t^j &= -|\mathbf{E}_t^j[\Delta S_t] - \Delta S_t| \\ &= -|\text{trunc}\left(\sum_{i=1}^{n} w_{i,t}^j x_{i,t}\right) - \Delta S_t|. \end{aligned} \tag{5.15}$$

We use the usual single-point crossover and the mutation operator with uniform probability. The crossover (resp., mutation) operation occurs at a certain rate (*crossover rate*, pcross) (resp., *mutation rate*, pmut).

Genetic algorithm can be interpreted economically as follows:

Each chromosome can be regarded as an agent's belief system about the exchange rate. That is, it represents which data are regarded as the important causes of the rate change. It must be noted that the belief systems can differ among agents.

In order to improve his prediction, each agent changes his own belief system with three operators: selection, crossover, and mutation (Fig. 5.3).

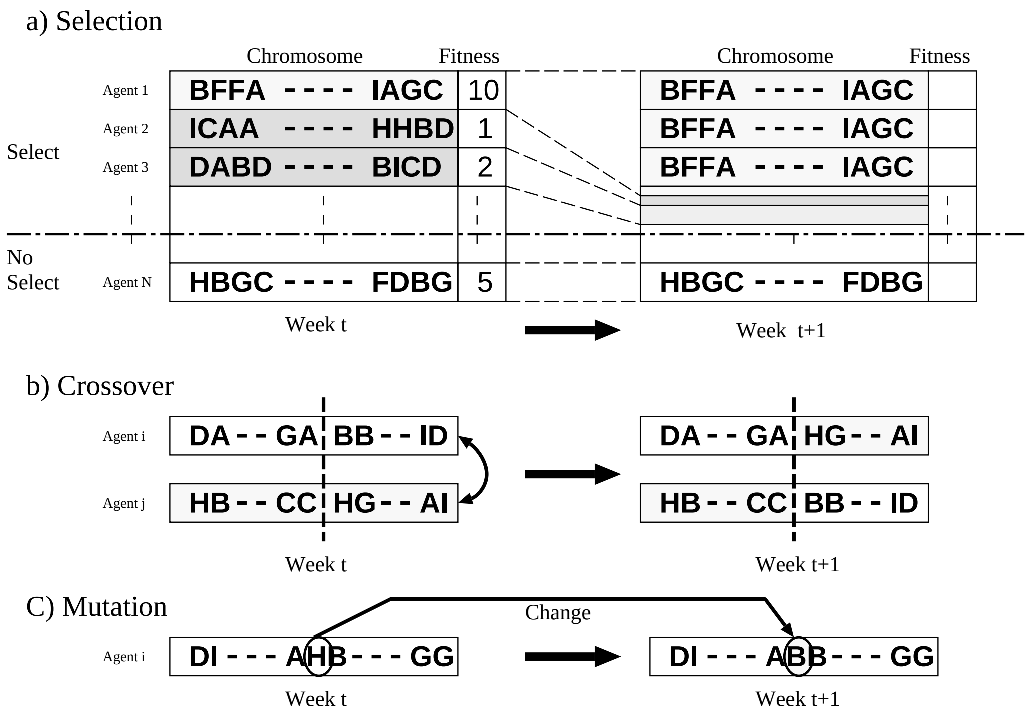


Figure 5.3: Genetic algorithm

The selection operator is regarded as the imitation of other agent's belief system which can predict the rate change more precisely. Therefore, belief systems predicting less precisely disappear from the market. Namely, it is regarded as the propagation of successful prediction methods. 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, and the mutation operator works like the independent change of each agent's prediction method.

AGEDASI TOF starts with the initial population which are randomly generated. During the first dozens of weeks (*training period*), it skips the rate determination step and uses the actual rate data as training data. And it computes the fitness of agents with the actual rate data. After this training period, it does not use the actual rate data at all and determines the equilibrium rates artificially in the rate determination step. And it computes the fitness with this artificial rate data instead of the actual rate data. Thus, after the training period, AGEDASI TOF uses only artificial data which are made by itself except the external data.

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

5.2 Algorithm

In this section, we would like to explain the flow of the algorithm of the model using an example in detail.

In the following example, let the number of this week **t**, logarithm of last week's rate is 5.20.

STEP 1: Perception

At first, each agent interprets raw data and perceives factors of rate change. In this week, the data are as below:

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

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

STEP 2: Prediction

After the perception, each agent predicts the rate change (mean and variance) using the weighted average of the news data in this week as the equations 5.16 and 5.18.

Agents **i**'s weights.

Interest	Trade	Stock	Trend
+0.5	−0.5	+0.1	+3.0

Agent **i**'s forecast:

$$
\begin{aligned}
\textbf{Mean} &= \text{trunc}\{\textstyle\sum(\text{Weight} \times \text{News})\} \times \text{scalingfactor} \qquad (5.16)\\
&= trunc\{(+2) \times (+0.5) + (-1) \times (-1.0) + (-3) \times (+0.1) + \\
&\qquad (+2) \times (+3.0)\} \times 0.02 \qquad (5.17)\\
&= +7 \times 0.02\\
&= +\mathbf{0.14} \leftarrow \text{Rise from 5.20}
\end{aligned}
$$

The scaling factor is calcurated from the ratio between the standard deviation of the rate change and that of the summation of weights and news.

$$
\begin{aligned}
\textbf{Variance} &= \frac{1}{\sqrt{\{\sum(Weight \times News > 0)\}^2 - \{\sum(Weight \times News < 0)\}^2}}\\
&= \frac{1}{\sqrt{\{2 \times +0.5 + (-1) \times (-1.0) + 3 \times 2.0\}^2 - \{-2 \times 0.1\}^2}}\\
&= \mathbf{0.125} \qquad (5.18)
\end{aligned}
$$

STEP 3: Strategy Making

Each agent decides, on the bases of his own prediction, his trading strategy (order to buy or sell dollar) as the equations 5.19, 5.20, and 5.21.

$$
\begin{aligned}
\text{Optimal amount of agent } \mathbf{i}'s \text{ dollar asset} &= \frac{\text{Forecast mean}}{\text{Forecast variance}} \qquad (5.19)\\
&= \frac{+0.14}{0.125}
\end{aligned}
$$

$$= \ +\mathbf{1.12}$$

The risk aversion in the equation 5.6 is set to be 1 for simplicity. It is a scaling factor of the trading amount in the step 4.

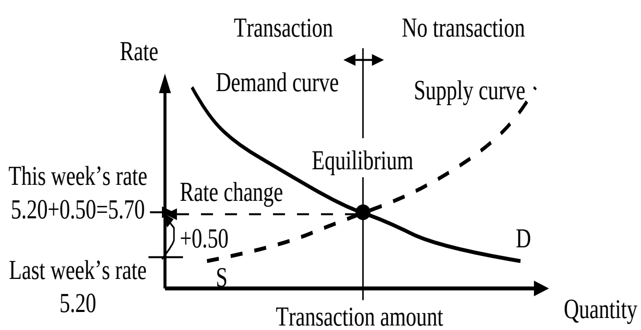
$$\begin{aligned}\text{Agent } \mathbf{i}'\text{s order quantity} &= (\text{Optimal amount}) - (\text{Last week}'\text{s amount}) \\ &= +1.12 - (-0.74) \qquad (5.20) \\ &= +1.86\ (\text{Buy}) \\ &\quad (+\ :\ \text{Order to buy},\ -\ :\ \text{Order to sell.})\end{aligned}$$

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

$$\text{Agent } \mathbf{i}'\text{s strategy} = \begin{cases} 1.86\ (\text{Buy}) & (\text{If rate} \leq +0.14) \\ \text{No Action} & (\text{If rate} > +0.14) \end{cases} \qquad (5.21)$$

STEP 4: Rate Determination

The demand and supply then determine the equilibrium rate, where quantity of demand and that of supply are equal.



Buyers(Sellers) with higher(lower) order rates can execute their exchanges and coincide their holding quantities with the optimal quantities. However, the other agents can not execute their exchanges and remains the previous holding quantity.

STEP 5: Adaptation

After the rate determination, each agent improves his prediction method using other agents' prediction. Our model uses GAs to describe the interaction between agents in learning .

$$\text{Agent } \mathbf{i}'\text{s Chromosome} = \{+\mathbf{0.5}, -\mathbf{1.0}, +\mathbf{0.1}, +\mathbf{3.0}\} \tag{5.22}$$

$$\begin{aligned} \text{Agent } \mathbf{i}'\text{s Fitness} &= -|(\text{Forecast mean}) - (\text{Rate change})| \\ &= -|(+0.14) - (+0.50)| \\ &= -\mathbf{0.36} \end{aligned} \tag{5.23}$$

$$\Downarrow$$

GAs (Selection,Crossover,Mutation)

$$\Downarrow$$

New weights

$$\Downarrow$$

STEP 1 in the next week t+1

Chapter 6

Simulation and Evaluation of the Model

6.1 Overview

In this chapter, we analyze the simulation results of the model in order to evaluate the model. We conduct the simulation using actual data of economic fundamentals in the real world. Then, we verify whether the model can explain emergent phenomena of the actual market in the three points: whether the rate dynamics produced by the model fit with that in the real world, whether the dealers' behavior patterns observed in the model fit with that in the field data, and whether the dealers' behavior patterns observed in the model can explain the rate dynamics. Finally the simulation results are compared with the field data in order to justify the simulation results.

The simulation is conducted as follows:

1. The proposed model is compared with other conventional market models. The out-of-sample forecast errors are used as a criterion of the

comparison. By this comparison, we can evaluate the model.

2. Using the model, we investigate the mechanism of the rate bubbles, which are one the emergent phenomena of markets. The model simulate the rate paths during the bubbles in 1990 and 1995. In the real world, there was a dollar appreciation bubble in 1990, and there was a yen appreciation bubble in 1995. About these two bubbles, the simulated data of agents' forecast, supply and demand, and rate dynamics are analyzed. Then the mechanism of the bubbles are proposed.

3. Phase transition of agents' forecast variety in simulated paths is examined. Each simulated path is divided into the two phases: a highly fluctuated period (a bubble phase) and a low fluctuated period (a flat phase). We investigate the dynamics of agents' beliefs, supply and demand. Then the mechanism of the phase transition is proposed.

4. Based on the idea, "the phase transition of forecast variety", we explain three emergent phenomena in markets: the contrary opinions phenomenon, rate change distribution depart from normality, and negative correlation between trading amounts and rate fluctuation.

5. For justification of the simulation results, the results are compared with the field data of the interviews and surveys in the three points: classification of factors, dynamics of weights, and mechanisms of the emergent phenomena.

6.2 Comparison with Other Models

In order to evaluate the proposed model, AGEDASI TOF, we compare it with other two models in out-of-sample forecasts accuracy. Other two models are a random walk model(RW) and a linear regression model(LR). Both LR and AGEDASI TOF consider the economic structure for construction of models, but RW does not reflect the economic structure. That is, the aims of these models are different. The aim of LR and AGEDASI TOF is to explain the mechanism of rate dynamics, while that of RW is only to forecast future rate without explanation.

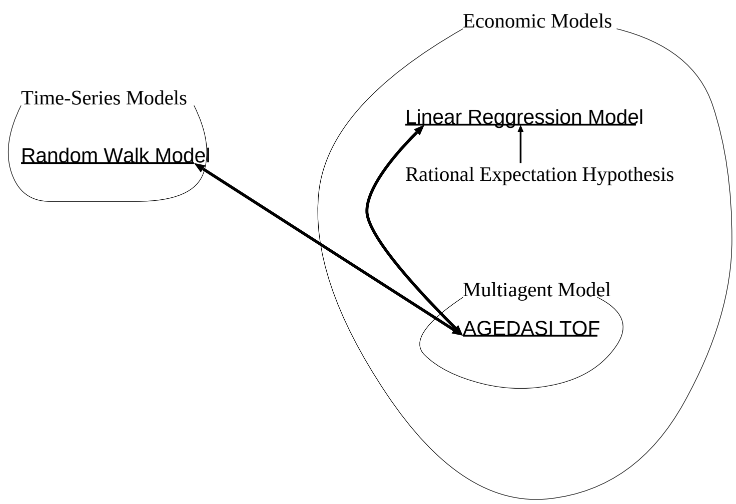


Figure 6.1: Comparison with Other Models.

LR uses the fundamentals and trend factors (Table 5.1) as explanatory variables. These factors include all variables used in many reduced-form equations of REH.

RW has a drift coefficient and use no explanatory variables. It must be noted that RW does not consider economical models of the market. We chose

RW among many time-series models because previous studies found that the the reduced-form equations of REH fail to improve on RW in out-of-sample forecasting [92].

6.2.1 A Method of Comparison

Comparison of models uses weekly data series between January 1986 and December 1993 in Tokyo foreign exchange market. These data series consist of the rate data and the 17 data in table 5.1. RW and LR are initially estimated using data through the first training 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 training 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. 6.2).

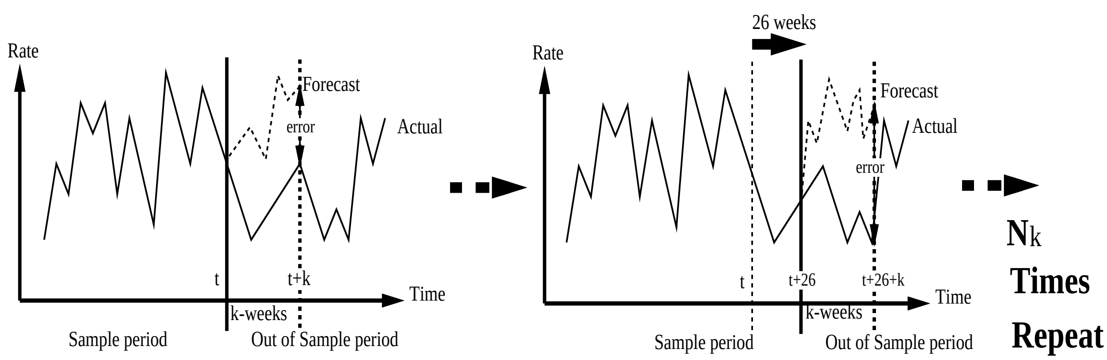


Figure 6.2: Out-of-sample forecast

In the same way, AGEDASI TOF is initially trained using the actual rate data and the 17 data through the first training period and forecasts are generated at the above five horizons. Then, extension of the training 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 (Gap=0.8,0.5,0.2). Forecast value under each parameter set is the average value over repetitions.

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

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

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

6.2.2 Results of Comparison

First, among the parameter sets (pcross=0.9,0.6,0.3; pmut=0.3,0.03,0.003; Gap=0.8,0.5,0.2), the parameter set, pcross = 0.3 pmut = 0.003, Gap = 0.8, is selected because forecast errors are the smallest under this parameter set (fig. 6.3, 6.4). In fig. 6.3, the errors of short-term forecasts are not so different. However, in fig. 6.4, both large probability of selection and small probability of both crossover and mutation are necessary for improvement of 3 months ahead forecasts. However, when both pcross and pmut were very small, the weights of all agents converged and the rate did not move. Thus, the probability of crossover and mutation must not be very small.

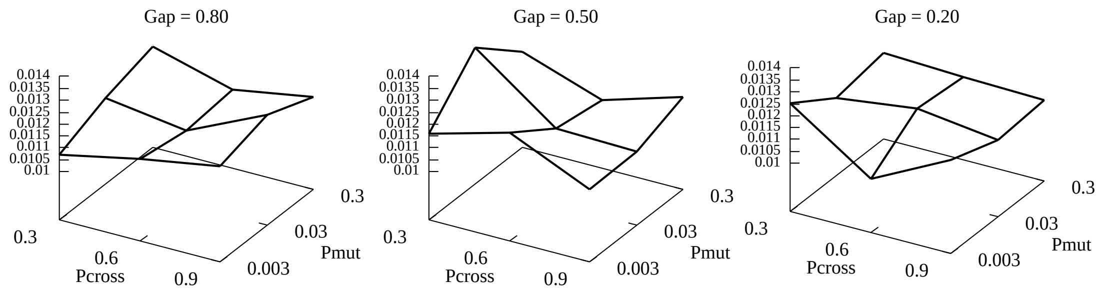


Figure 6.3: RMSE under different parameter sets. (The forecast horizon is 1 week.)

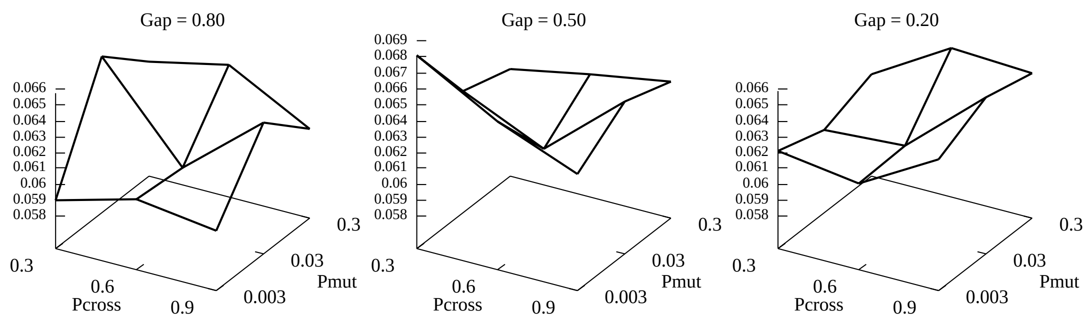


Figure 6.4: RMSE under different parameter sets. (The forecast horizon is 13 weeks.)

Results of the comparison indicate that both MAE and RMSE of AGEDASI TOF are the smallest over all horizons and all parameter sets. Table 6.1 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 (RMSE) of AGEDASI TOF are smaller over 12%(6%) than MAE (RMSE) of RW. And the larger the forecast horizon, the better AGEDASI TOF forecasts 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.

	MAE			**RMSE**		
	RW	LR	AGEDASI TOF	RW	LR	AGEDASI TOF
k=1	0.98	1.19	0.86	1.16	1.39	1.09
		(+21%)	(-12%)		(+20%)	(-6%)
k=4	1.33	3.05	0.94	1.73	3.83	1.25
		(+130%)	(-29%)		(+121%)	(-28%)
k=13	6.27	7.44	5.43	6.91	8.52	6.32
		(+19%)	(-13%)		(+23%)	(-9%)
k=26	8.60	10.46	6.48	9.59	12.41	7.90
		(+22%)	(-25%)		(+29%)	(-18%)
k=52	10.59	11.41	7.33	14.21	16.77	8.33
		(+8%)	(-31%)		(+18%)	(-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 6.1: Comparison of models

6.3 Rate Bubbles

In this section, we investigate the mechanism of the rate bubbles, which is one of the emergent phenomena of markets. The model simulates the rate paths during the bubbles in 1990 and 1995. In the real world, there was a dollar appreciation bubble in 1990, and there was a yen appreciation bubble in 1995. About these two bubbles, the simulated data of agents' forecast, supply and demand, and rate dynamics are analyzed. Then the mechanism of the bubbles are proposed in section 6.3.3.

6.3.1 Analysis of the Bubble in 1990

Simulation Methods

In order to analyze the rate change of AGEDASI TOF and to compare it with actual data, we generate out-of-sample forecast paths. First, AGEDASI TOF is initially trained using the actual rate data and the 17 data in table 5.1 through a training period. Next, using only the external data (no. 1-14 in table 5.1), an out-of-sample forecast path is generated through a forecast period. In this section, the training period is between January 1986 and December 1987 and forecast period is between January 1988 and December 1993. Under the best parameter set (*pcross*=0.3, *pmut*=0.003, *G*=0.8)[1], the above procedure is repeated 50 times and 50 forecast paths are generated.

Bubble and Non-Bubble Group

The results of out-of-sample forecasts are divided into two groups since 1990: a *bubble group* and a *non-bubble group* (Fig. 6.5). In the bubble group, the exchange rate rises in 1990, collapses in 1991, and returns to the previous level in 1992. 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. 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. The actual path of the exchange rate has a bubble and a collapse. Hence it belongs to the bubble group.

[1] Under this parameter set, forecast errors are the smallest.

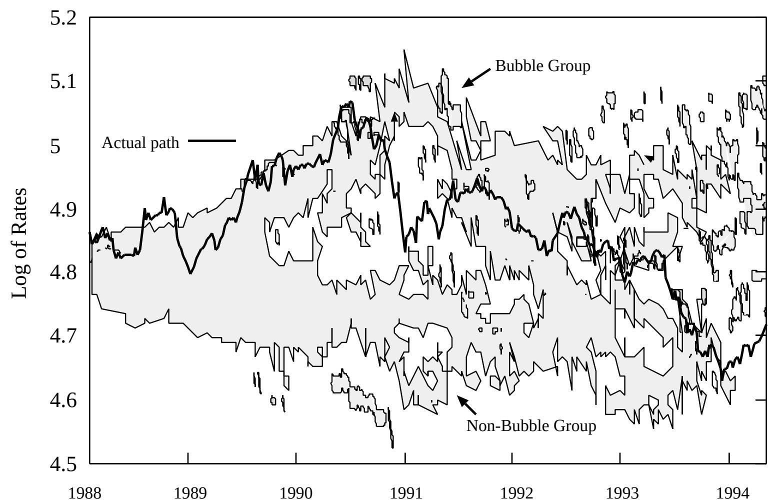


Figure 6.5: Distribution of simulated paths: the paths move in the dotted areas.

Factors' Weights

In order to investigate causes of the bubble, we compare between the data 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 fact, the bubble case has a bubble and a collapse, and the non-bubble case does not.(Fig. 6.6). The market averages are calculated about the weights of the 17 data in the bubble case and the non-bubble case (Fig.6.7). In the bubble case, the average of Economic Activities data weights is stably around 1.5. That of Intervention data weights has a large plus value. This indicates that intervention had a reverse effect: the buying-dollar intervention causes dollar depreciation. As a whole, absolute value of the market averages of the external data weights in the bubble case are larger than in the non-bubble case. That is, agents in the bubble case are more sensitive to the external data than in the non-bubble case. Moreover, in the bubble case the average of Short-Term Trend data

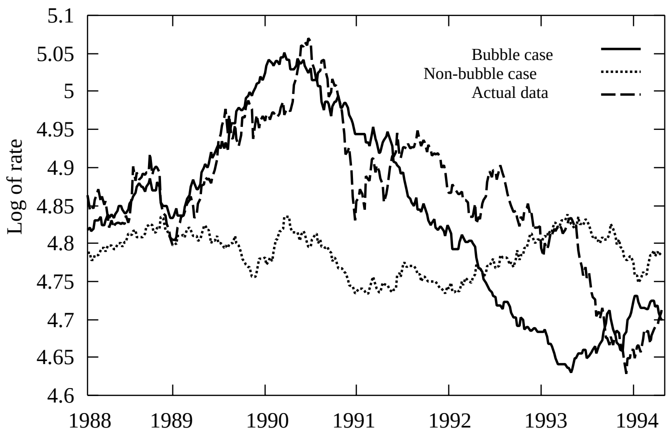


Figure 6.6: Rate paths

(ΔS_{t-1}) weight keep a plus value from during the bubble and the collapse, and the average of Long-Term Trend data ($S_{t-1} - S_{t-6}$) weight has minus value (Fig. 6.8). This implies 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

Next, we investigate supply and demand curves and dealing quantity around the collapse in the bubble case (Fig.6.9). When the bubble grows, demand quantity is much larger than supply quantity (July 1989 and January 1990). When the bubble collapses in March 1990, dealing quantity is almost zero because of absence of supply. After the collapse (July 1990), supply quantity is larger than demand quantity.

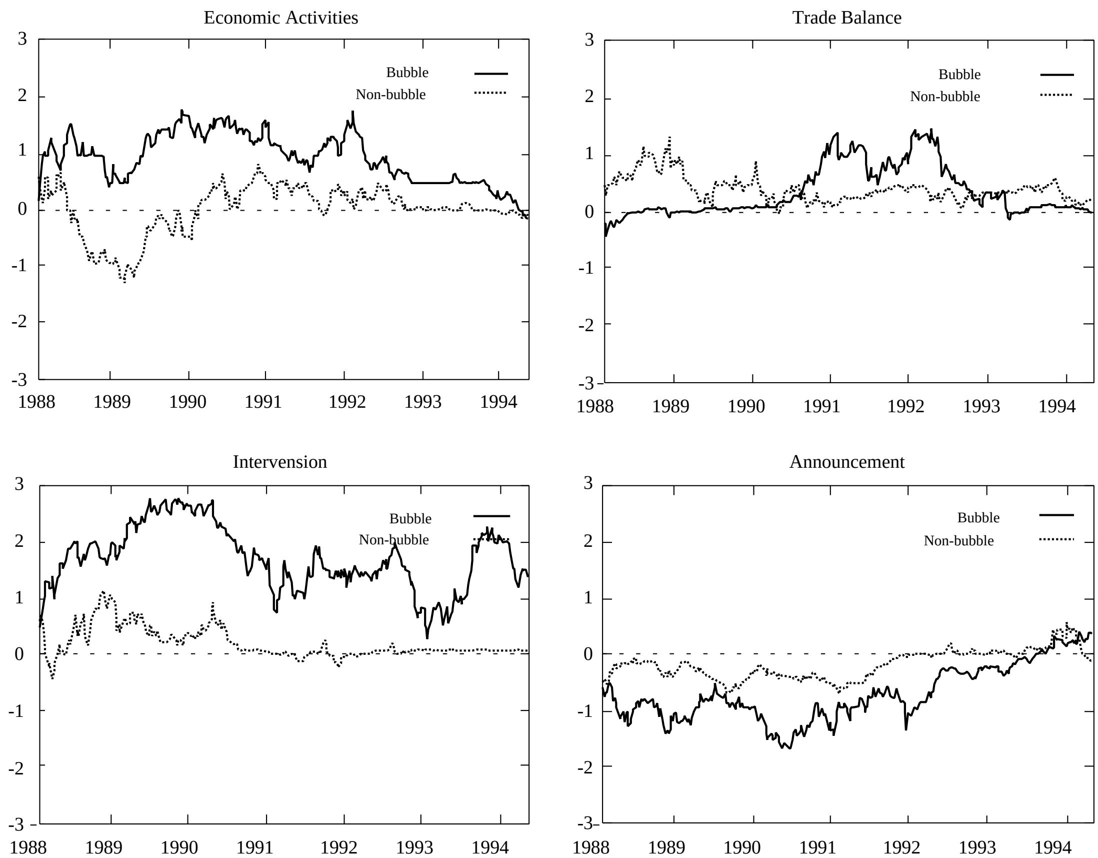


Figure 6.7: Market Average of External Data Weights

6.3.2 Analysis of the Bubble in 1995

To examine the emergent phenomena of the market, we conducted extrapolation simulations of the rate dynamics from January 1994 to December 1995.

Simulation Method

Initialization The initial population is a hundred agents whose weights are randomly generated.

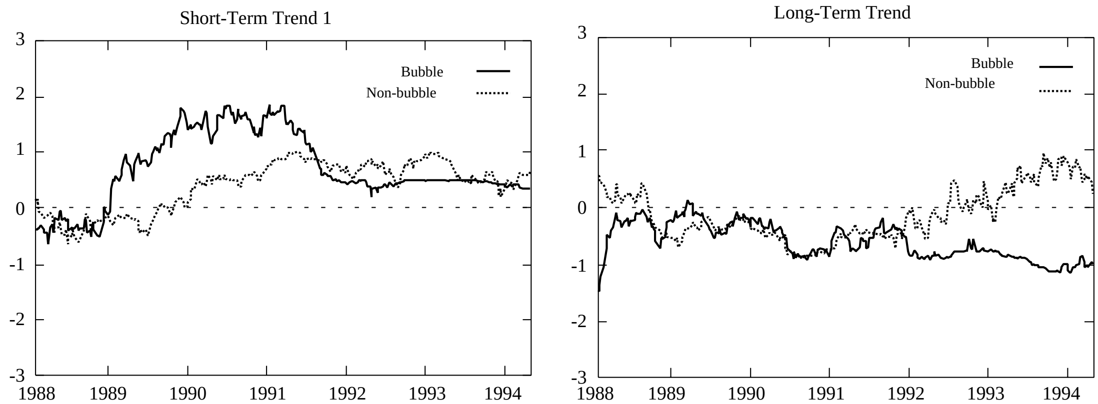


Figure 6.8: Market Average of Internal Data Weights

Training Period We trained our model by using the 17 data (Tab.5.1) in the real world from January 1992 to December 1993. But during this *training period*, we skipped the Rate Determination Step and in the Adaptation Step we used the cumulated value of the differences between the forecast mean of each agent and the *actual rate* as his fitness of GAs. Each weekly data of these two years was used a hundred times, so in the training period there were about ten thousand generations.

Forecast Period For the period from January 1994 to December 1995 we conducted the extrapolation simulations. In this *forecast period*, the model forecasted the rates in the Rate Determination Step by using only the external data. We didn't use any actual rate data, and both the internal data in the Perception Step and the fitness in the Adaptation Step were calculated on the basis of the rates which were generated by our model in the Rate Determination Step.

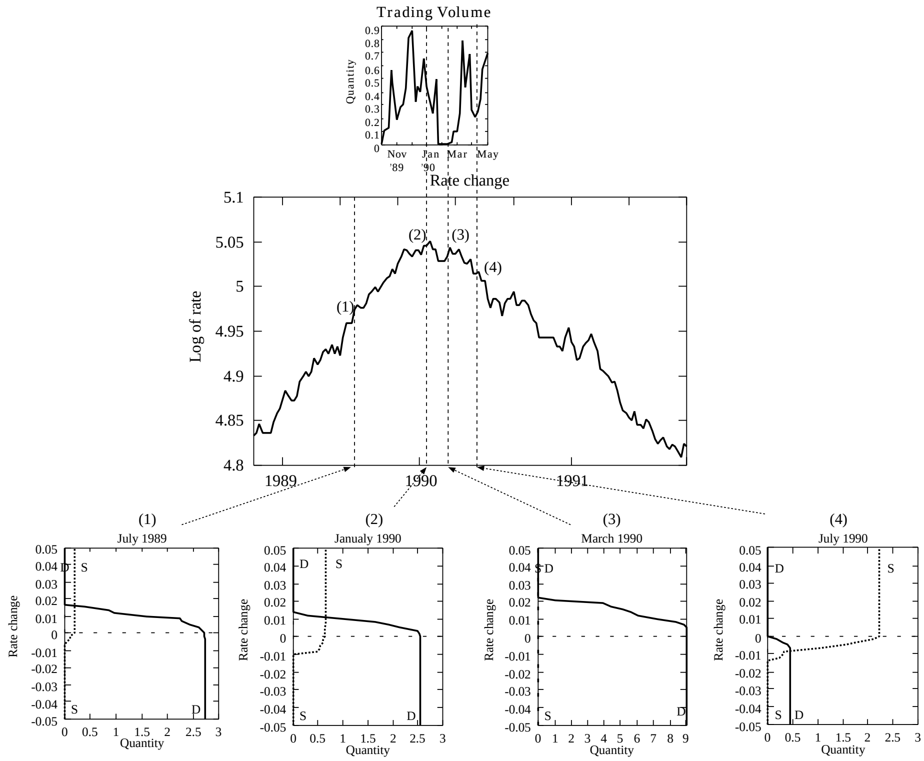


Figure 6.9: Supply and Demand Curves and Quantity

We repeated this procedure a hundred times in order to generate a hundred simulation paths[2].

Overview of the Results

As the results of the simulations, numbers of simulation paths in each trend, in each period of Tab.4.1, are presented in Tab.6.2. Most of the simulation paths are moving in the same direction as the actual path.

[2]We used the following parameter sets: pcross=0.3, pmut=0.003, G=0.8. The simulation suffered from the smallest forecast errors by using this set in our preceding study.

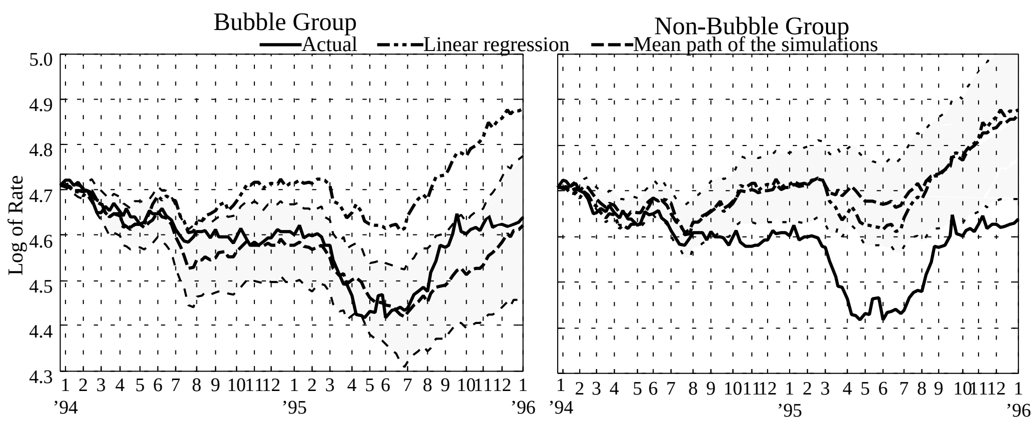
	I	II	III	IV	V	VI	VII	VIII	IX
↗	4	0	22	20	**25**	5	**34**	**73**	72
→	**70**	66	**65**	**76**	41	44	53	23	**26**
↘	26	**34**	13	4	32	**51**	13	4	2

The boldfaced parts show the same trend as the actual path.
The trend criterion is a mean weekly growth rate: ±0.3%.

Table 6.2: Numbers of simulation paths in each trend.

Bubble Group vs. Non-Bubble Group

From Period VI to Period VIII (from February to September in 1995), 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.6.10a), and the *non-bubble group*, in which the paths don't have such a bubble (Fig.6.10b). The



The dotted areas denote the mean ± one standard deviation

Figure 6.10: Distribution of simulation paths.

bubble group occupies 25% of all the simulation paths, and the non-bubble group occupies 75%.

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 moves in a way similar to that in which the mean path of the non-bubble group moves. The linear regression path and the actual path have the same trend in each period[3], so, the configuration of the actual rate path seems to be determined mainly by the external data. But, the rate bubble seems to be caused by other reasons.

We investigated the conditions that cause the bubble by comparing the market averages of the data weights in the bubble group paths with those in the non-bubble group paths. First we chose the four external data that have the largest absolute values of the market averages, and we compared the time variances of these data in the bubbles group with those in the non-bubble group (Tab.6.3a). The result is that the variances of the bubble group are significantly larger than those of the non-bubble group. Namely, one of the conditions of the bubble is that the interpretations of the external data in the market change flexibly from one period to another period. We also compared the time average of the internal data weights in the bubble group with those in the non-bubble group (Tab.6.3b). The result is that the averages of the bubble group are positive, whereas those in the non-bubble group are negative and that the differences are significant. That is, that the agents forecast that recent chart trend will continue (the bandwagon expectations) is also a condition of the bubble.

We chose one typical path[4] of the bubble group. We analyzed the market averages of this path's weights and found that the internal data weights in the bubble period are twice as large as those in the other periods. That is,

[3]But the widths of the fluctuations are different (Fig.6.10).

[4]This path is typical in that its movement and its weights' movement are similar to those of the mean path of the bubble group.

a) External data: Comparison of time variance

	Price	Interest	Intervention	Announcement
BG	1.279	1.210	0.759	0.923
NBG	1.152	1.077	0.413	0.336

b) Internal data: Comparison of time average

	Short-term Trend 1	Long-term Trend
BG	0.105	0.113
NBG	−0.102	−0.229

(BG=Bubble Group, NBG=Non-Bubble Group)
All differences are significant at the 99.9% level.

Table 6.3: Comparisons.

both the inflation and collapse of the bubble are caused by the bandwagon expectations[5].

We also examined the supply and demand curves and trading volume during the bubble in this typical path (Fig.6.11). When the bubble grows, the supply is much larger than the demand (Fig.6.11c). When the bubble stops, the transaction amount is almost zero because of the absence of demand (Fig.6.11d). During the collapse, the demand is larger than the supply (Fig.6.11e).

6.3.3 Mechanism of the Rate Bubbles

Considering all the above results in section 6.3.1 and 6.3.2, one plausible mechanism which brought about the bubble can be regarded as the following sequence:

[5]Positive values of the internal data weights imply that agents ride along with the recent trend.

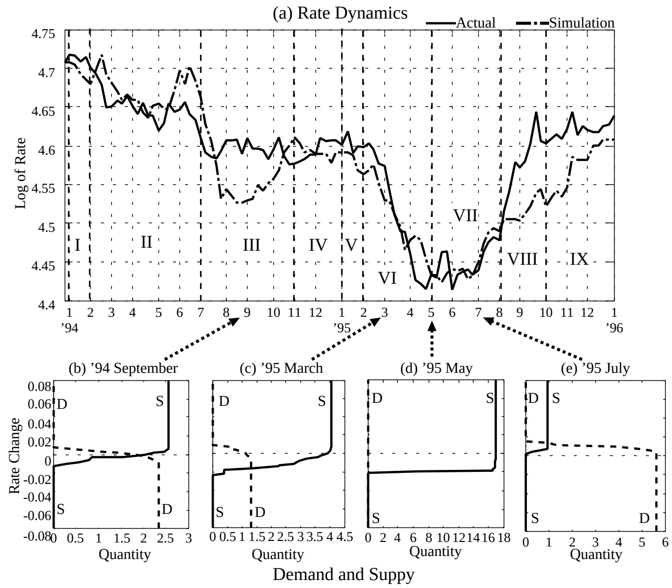


Figure 6.11: Rate change and demand-supply curves.

1. It is determined mainly by the external data when the bubble starts to grow.

2. The bubble grows because of the bandwagon expectations: most agents expect that the recent trends, which are caused by external data, will continue.

3. The bubble stops growing because almost all agents expect the rate to decrease and because no one wants to buy. Then the transaction amount becomes zero.

4. Because of the stop of the bubble's growth, the trend vanishes. When the external data make the reverse trend, the bubble collapses because of the bandwagon expectations.

6.4 Phase Transition of Forecasts Variety

In this section, in order to analyze the other emergent phenomena than the rate bubbles, the phase transition of agents' forecast variety in the simulated paths is examined. To do so, we analyze five simulation paths which are selected randomly from the bubble group in the simulations of the bubble in 1995. These five simulation paths occupy 20 % of the bubble group, because there are 25 simulation paths in the bubble group.

First, each simulated path is divided into two phases: a highly fluctuated period (a *bubble phase*) and a low fluctuated period (a *flat phase*). Second, we investigate differences of agents' beliefs between the two phases in each simulation path. Third, the demand-supply conditions are also examined. Finally, the mechanism of the phase transition is proposed.

In the following sections, we illustrate the results of the above analysis considering one typical path. However the pattern of these results are common among the selected five paths.

6.4.1 Flat Phase and Bubble Phase

As shown in Fig.6.12, each simulated path in the bubble group is divided into two phases: a highly fluctuated period and a low fluctuated period. The simulated rate moves flat from March 1994 to December 1994, while the rate drop quickly and then rise dramatically from January 1995 to December 1995. The low fluctuated period, from March 1994 to December 1994, is defined as *flat phase*. The highly fluctuated period, from January 1995 to December 1995, is defined as *bubble phase*.

Are there other differences between these two phases? In order to answer

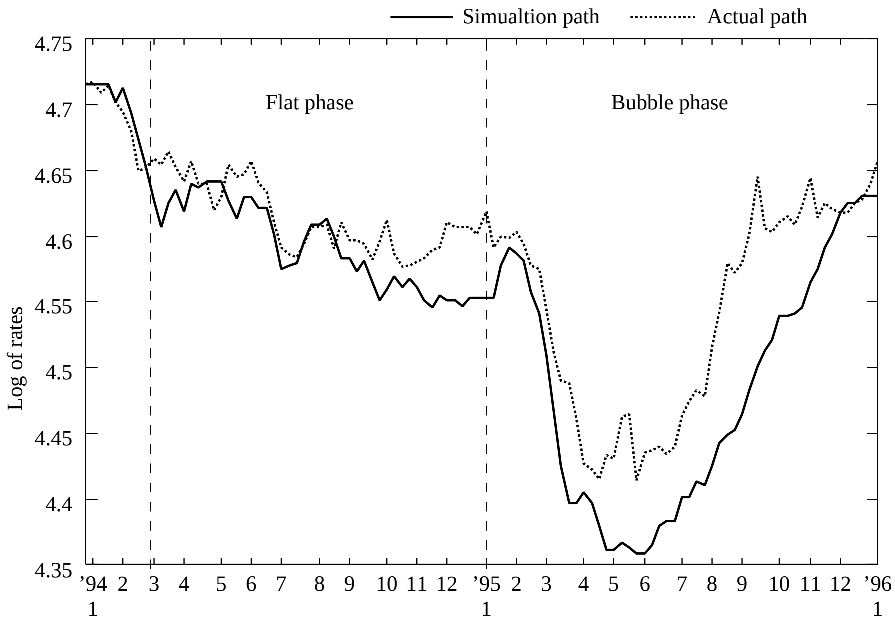


Figure 6.12: Rate dynamics of the simulation path

the question, we compare between the two phases and figure out the features of each phase in the following sections.

Distribution of forecasts

First, distribution patterns of agents' forecasts are compared between the two phases. Fig.6.13 shows percentage of agents who forecast a rise of dollar and that of agents who forecast a drop of dollar, in the form of four weeks averages.

In the flat phase, the distribution of forecasts is balanced: the number of agents who forecasts a strong dollar is almost the same as that of agents who forecasts a weaker dollar. By contrast, in the bubble phase, the distribution of forecasts is one-sided: almost 80 % of all agents forecast that the dollar will rise in the first half of 1995, while near 80 % of all agents forecast that

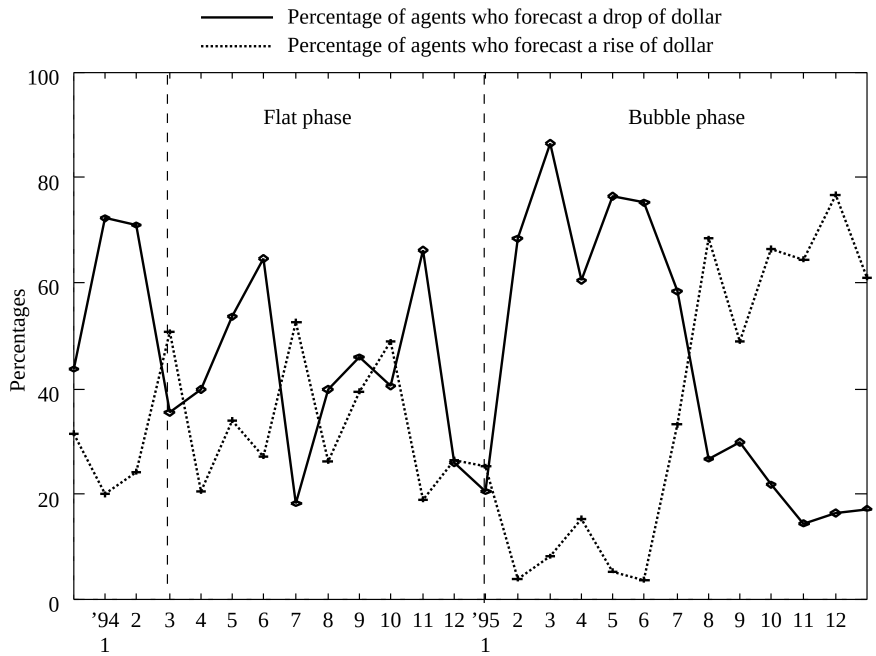


Figure 6.13: Percentages of agents' forecasts

the dollar will drop in the latter half of 1995. In other words, the *variety of forecasts* is rich in the flat phase because there are forecasts of both sides in the market. The variety of forecasts, however, is poor in the bubble phase because many forecasts in the market converge to only one side.

Trading amounts

Second, the supply and demand relationships are compared between the flat phase and the bubble phase.

A typical pattern of supply and demand in the flat phase is illustrated in Fig.6.14a. In the flat phase, the amounts of dollar supply and demand are balanced. Hence, they meets around the same rate as the last weeks' rate. The trading amounts at the equilibrium rates are larger in the flat phase.

This is because there are plenty amounts of both supply and demand.

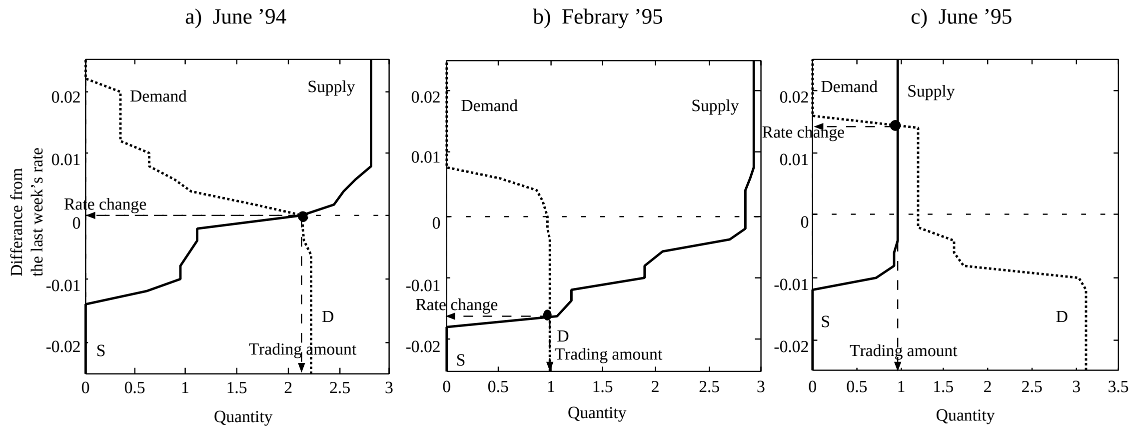


Figure 6.14: Supply and demand

Typical patterns of supply and demand in the bubble phase are illustrated in Fig. 6.14b,c. In the first half of the bubble phase, the sell orders of dollar rush into the market. By contrast, in the latter half, there are many buy orders in the market. Throughout the bubble phase, the trading amounts are smaller, because the opposite orders are not provided sufficiently in the market.

In order to verify that the trading amounts in the flat phase are larger than those in the bubble phase, the difference of the average of the trading amounts between the two phases is checked by t-test. The result is shown in table 6.4. The trading amounts in the flat phase tend to be larger than that in the bubble phase ($P < 0.1$).

Rate Fluctuation

Finally, the difference of the rate fluctuation is also examined. The means of absolute values of monthly rate changes are calculated both in the flat

	flat phase	bubble phase
Number	44	52
Mean	0.745	0.549
Variance	0.445	0.654
t value	1.307	
Probability	0.0972	

Table 6.4: Difference of trading amounts

phase and the bubble phase. The difference of these means is checked by t test (table 6.5). The result is that rate fluctuation in the bubble phase is significantly larger than that in the flat phase ($P < 0.05$).

	flat phase	bubble phase
Number	11	13
Mean	0.00149	0.000742
Variance	9.87×10^{-5}	7.42×10^{-4}
t value	2.23	
Probability	0.0200	

Table 6.5: Difference of fluctuation

Features

Let us summarize the main points of the results in the above sections. The features of the flat and bubble phases are listed in table 6.6.

	flat phase	bubble phase
Distribution of forecasts	Balanced	One-sided
Variety of forecasts	Rich	Poor
Trading amounts	Large	Small
Fluctuation	Small	Large

Table 6.6: Features of flat and Bubble phase

In the flat phase, agents' forecasts distribute symmetrically around the last week's rate. In other words, the variety of forecasts is rich because there are forecasts in both sides. The amounts of supply and demand are balanced, so the trading amounts are larger at the equilibrium. Supply and demand tend to meet around the last week's because there are sufficient amounts of supply and demand around the the last week's rate. Hence, the rate fluctuation is smaller in the flat phase.

In the bubble phase, agents' forecasts lean to one side. That is, the variety of forecasts is poor because most agents have the same forecasts. The amounts of supply and demand are one-sided, so the trading amounts are smaller at the equilibrium. Supply and demand tend to meet apart from the last week's because there are not sufficient amounts of opposite orders around the last week's rate. Hence, the rate fluctuation is larger in the bubble phase.

6.4.2 Data weights

In this section, the dynamic patterns of the data weights which agents have are investigated, in order to know the mechanism of the phase transition.

First, the data weights are classified into six factors as a result of factor analysis of their dynamic patterns. Then, we divide these six factors into three categories based on their meanings. Next, about each category, the following matters are examined: differences of its value between the flat phase and the bubble phase, temporal changes of agent groups, and distribution patterns in the market.

Classification of Data Weights

In order to outline the dynamic pattern of agents' learning, the data weights which agents have are classified into six factors as a result of factor analysis of their dynamic patterns.

First, the matrix which is analyzed by factor analysis is constructed. Twelve data (table 6.7) are selected from the seventeen data in table 5.1. Five data are discarded because they are alway zero during the forecast period or both their market average and variance are so small that they have little influence on the rate change. The matrix is a list of 12 weights of 100 agents every 10 week during the forecast period. Thus, the width of matrix is 12, the height is 100 (agents) $\times$ 11 (weeks). Because this matrix includes the weight value in different weeks, it can represent the temporal change of weights.

Second, factors are extracted by principal component analysis. As a result, we consider that top six factors which have the largest eigenvalues are appropriate as extracted factors. The proportion of explanation by these six factors is 67.0 %.

Finally, we extracted six factors from the twelve data by factor analysis. Then these six factors are rotated by Varimax rotation and each factor is interpreted from loading value of its component data. The loading value after Varimax rotation is shown in table6.7.

The interpretation and classification of these six factors are shown in table 6.8.

The first factor has large absolute value of Economic activities data and Price data. These two data are used by the price monetary approach, which is one of the classical econometric approaches of exchange markets. The price

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Economic activities	**−0.5256**	−0.0040	−0.0335	0.0869	−0.0032	0.0063
Price	**0.5009**	0.1347	−0.1498	0.1431	0.2047	0.0305
Interest	0.0624	0.0795	**−0.3578**	−0.0271	−0.0189	0.0212
Trade	0.0396	0.1302	**0.4885**	0.1144	0.0043	0.0515
Employment	0.2006	−0.0814	0.2497	**0.3719**	**0.3662**	0.1263
Intervention	-0.0838	0.0035	0.2265	0.2358	**−0.4132**	0.2070
Announcement	0.0259	−0.0572	0.0800	**0.4970**	−0.0884	0.0314
Mark	−0.0232	−0.0070	0.0795	−0.1008	−0.0514	0.0676
Politics	0.0431	−0.0381	0.0802	−0.0858	**0.3751**	0.0567
Stock	0.0369	**−0.4688**	−0.0837	0.0356	0.0295	0.2283
Short-term trend 1	0.0897	**0.5628**	−0.0694	−0.0330	−0.0268	0.0956
Long-term trend	−0.0008	−0.0380	0.0153	0.0712	−0.0022	**0.4938**

The numbers whose absolute values are more than 0.350 are underlined.

Table 6.7: Loading value

Categories	Factors (members of categories)	Data (members of factors)
Econometrics	1. Price monetary	Economic activities, Price
	3. Portfolio balance	Trade, Interest
News	4. Announcement	Announcement, Employment
	5. Politics	Intervention, Politics, Employment
Trend	2. Short-term	Short-term trend 1, Stock
	6. Long-term	Long-term trend

Table 6.8: Categories of factors

monetary approaches mainly deal with national price level and domestic economic situation. Thus, the first factor is named as *Price monetary* factor.

The second factor consists of Short-term trend data and Stock data. From 1994 to 1995, stock markets have the similar trend to the exchange markets. Hence, this factor represents the short-term trends common to these markets. We call this factor *Short-term* factor.

The third factor concerns the Trade data and Interest data. These two data are included in the portfolio balance approach, which is also the traditional econometric model of exchange markets. The central feature of the portfolio balance approach is that it distinguishes between domestic and foreign assets as imperfect substitutes. Hence, its model mainly focused on trade and interest indices. The third factor is defined as *Portfolio balance* factor.

The fourth factor has large absolute value of Announcement data and Employment data. Because the loading value of the Employment data is relatively smaller than that of Announcement factor and the market average of the Employment data weight is smaller during 1994 to 1995, we call the fourth factor as *Announcement* factor.

The fifth factor consists of Intervention, Politics, and Employment data. Because of the same reason as the Announcement factor and these data meaning, The fifth factor is defined as *Politics* factor.

The sixth factor concerns the Long-term trend data. We call it as *Long-term* factor.

These six factors are categorized as shown in table 6.8. Because the Price monetary factor and Portfolio balance factor have the same focuses as econometric models, they are categorized as *Econometrics* category. Both the Announcement factor and Politics factor deal with political and social news. Thus they are included in *News* category. The Short-term factor and Long-term term factor concern about chart trends. Hence *Trend* category consists of these two factors.

Next, about dynamic patterns of each category, the following matters are examined: differences of its value between the flat phase and the bubble phase, temporal change of agent group, and distribution patterns in the market.

Econometrics category

Fig.6.15 illustrates market averages of all agents' scores of the Price monetary factor and Portfolio balance factor. These factors are relatively stable during the flat phase and bubble phase. About the Price monetary factor, almost all agents have the same value of its score after June 1994. However, its influence on rates is not so large, because its absolute value is small. On the other hand, concerning the Portfolio balance factor, the absolute values of its market averages are large. Especially, during the first half of the bubble phase, they are roughly twice as before.

The distribution patterns of agents' scores of the Price monetary factor and Portfolio balance factor are illustrated in fig.6.16a and 6.16b. The distribution patterns in the flat phase (fig.6.16a) and in the bubble phase (fig.6.16b) are very similar, except that scores of the Portfolio balance factor shift down.

In order to get more detailed illustration of temporal change of the Econometric category, first, we examine the frequencies of agents who have plus (minus) value of the component data of the Econometric category. The

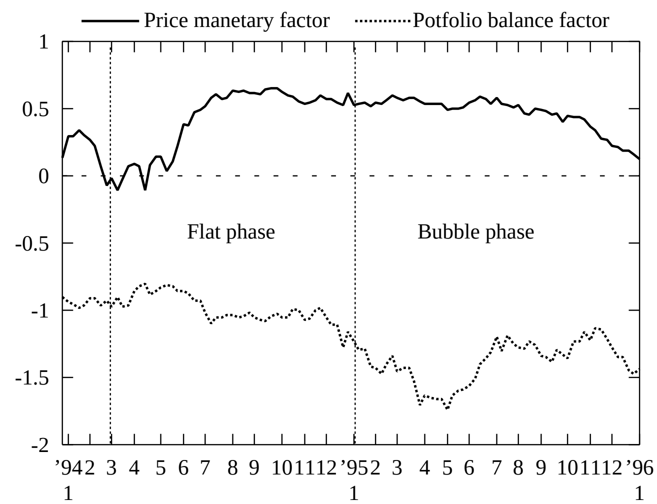


Figure 6.15: Temporal change of Econometrics category

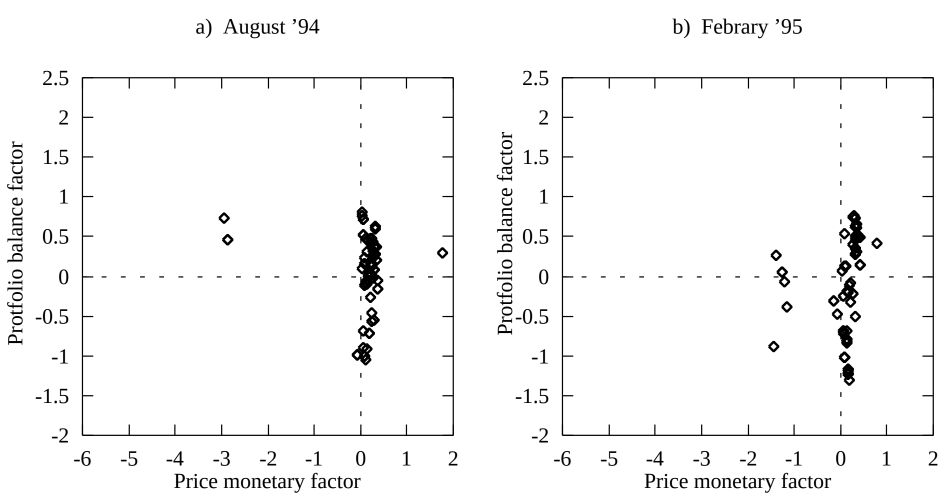


Figure 6.16: Distribution of scores of Econometric category

result is that opinions about all four component data (Economic activities, Price, Trade, and Interest) are common in the market and stable. It is because more than 80 % of agents have the same positive (or negative) weights throughout the flat and bubble phase.

Second, market averages of its component data are investigated (fig.6.17). The weights of the Economic activities data and Interest data are so small

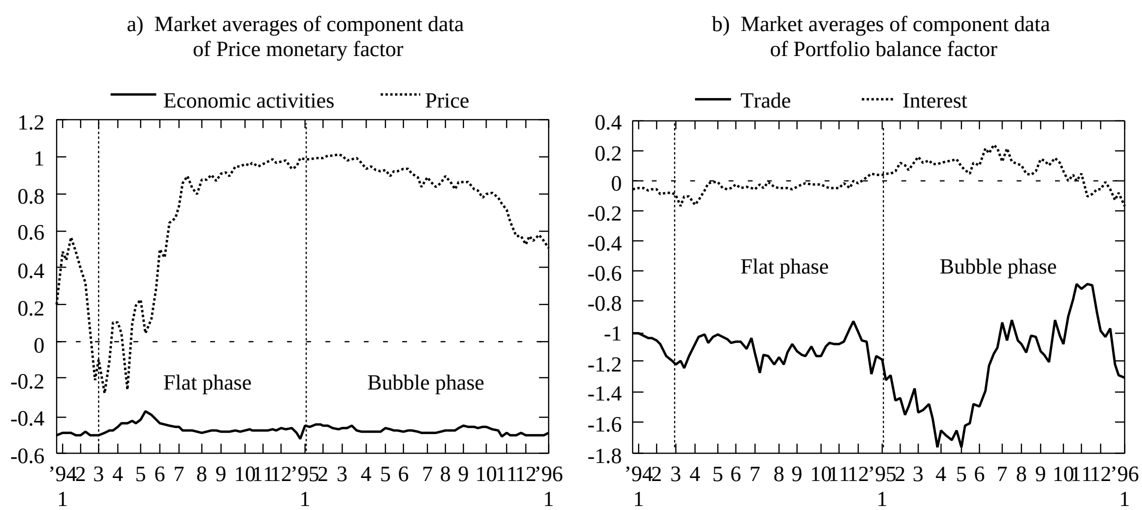


Figure 6.17: Market averages of component data of Econometric category

that they have little influence on the rate dynamics. Because there are very few data about the Price data, it also doesn't have large contribution to the rate dynamics. From December 1994 to March 1995, there is a sharp increase of the absolute value of the Trade data weight. This implies that agents paid attention to the Trade data especially just before the yen appreciation bubble started.

The correlation coefficient between the Trade data and rate changes is the largest among the component data of Econometric categories from June 1994 to April 1995 (table6.9). This fact implies that the agents regarded the

Trade	Economic activities	Price	Interest
−0.229	0.030	−0.048	0.147

(From June 1994 to April 1995)

Table 6.9: Correlation coefficients between the Econometric category and the rate change

Trade data as more important just before the bubble started because the Trade data could explain the rate change better than the other data.

News category

Fig.6.18 illustrates market averages of all agents' scores of the Announce and Politics factor. The absolute value of these factors' weights rapidly increased just before the rate bubble started. That is, they were not so paid attention in the flat phase. However from the end of the flat phase to the bubble phase, they are recognized as important factors.

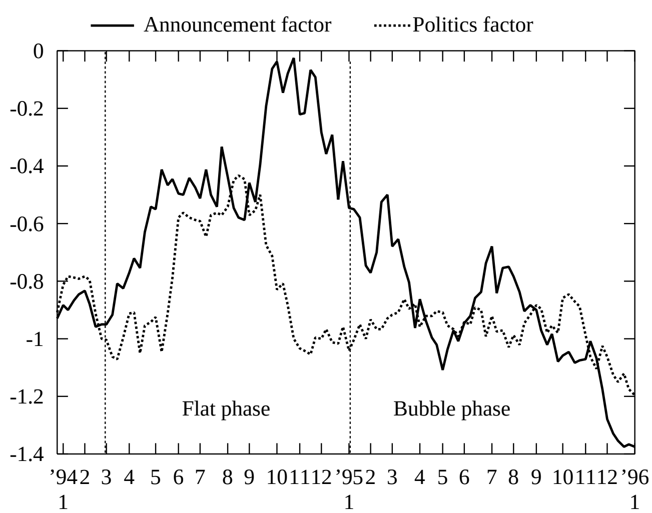


Figure 6.18: Temporal change of News category

The distribution patterns of agents' scores of the Announcement factor and Politics factor are illustrated in fig.6.19a and 6.19b. The distribution patterns in the flat phase (fig.6.19a) and in the bubble phase (fig.6.19b) are clearly different. In the flat phase, the scores spread widely, while in the bubble phase, they shifted to left and bottom areas.

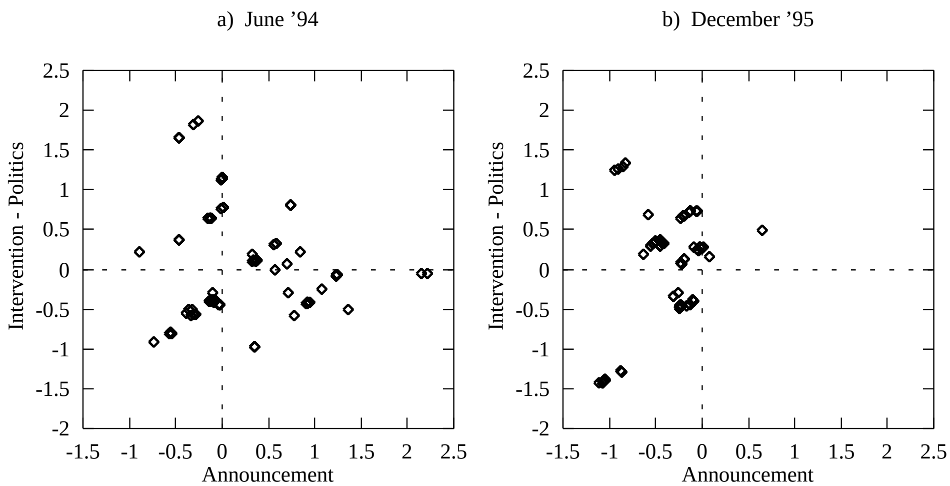


Figure 6.19: Distribution of scores of News category

Let me turn to more detailed illustration of temporal change of the News category. In fig.6.20, the market averages of its component data are shown. The weights of the Employment data and Intervention data are so small that they have little influence on the rate dynamics. Around the end of the flat phase, the absolute weight values of the Announcement data and the Politics data increase quickly. In the bubble phase, almost all agents have the minimum weight value -3 of these data. That is, the market consensus that these two data are the most important was established in the bubble phase.

In order to verify the convergence of market opinions, we examine the frequencies of agents who have minus weight value of the Announcement

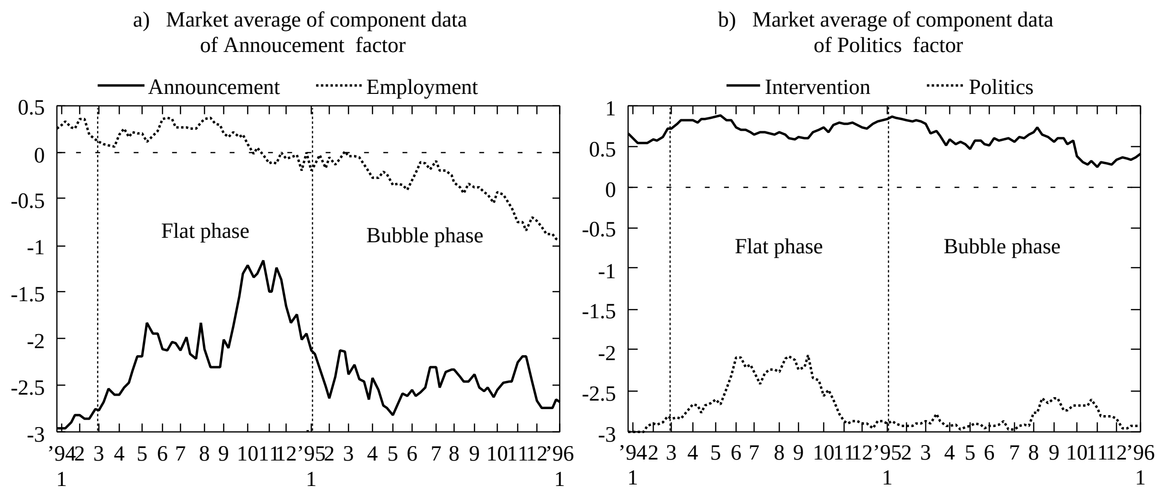


Figure 6.20: Market averages of component data of News category

data and the Politics data (fig. 6.21). The result is that the very strong market consensus is established since the end of the flat phase. Over 90 % of agents have minus weights of these data in the bubble phase.

The correlation coefficient between component data of the News category and rate changes is much larger than the other data from June 1994 to April 1995 (table 6.10). The large correlation made market opinions about these

Intervention	Announcement	Politics	Employment
0.377	−0.293	−0.318	−0.032

(From June 1994 to April 1995)

Table 6.10: Correlation coefficients between the News category and the rate change

data converge.

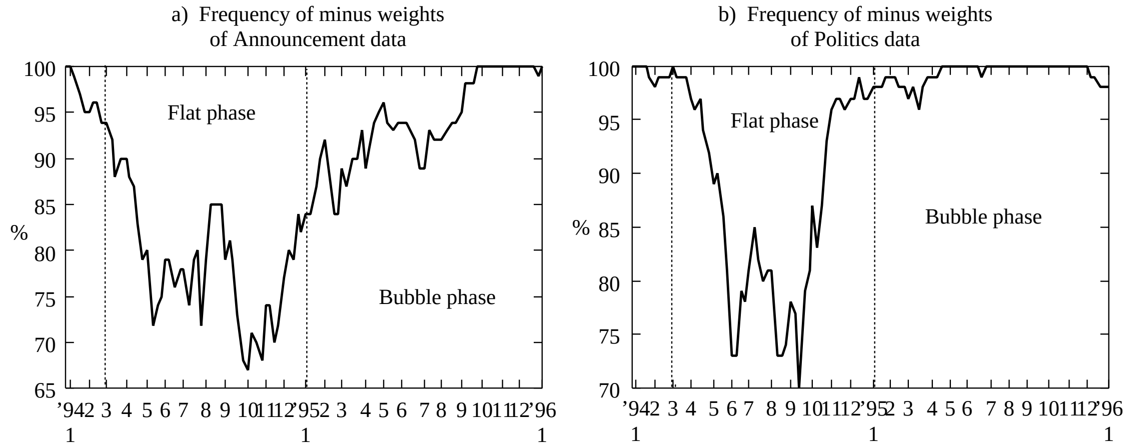


Figure 6.21: Frequency of minus weights

Trend category

Fig.6.22 illustrates market averages of all agents' scores of the Short-term factor and Long-term factor. These factors show distinctive dynamic patterns. About the Short-term factor, the market average continuously rose to the plus until May 1995. After it fluctuated at the plus, it returned to the minus in December 1995. By contrast, concerning the Long-term factor, its market average moves steadily until June 1995. Since July 1995, it drops to the lowest level.

The distribution patterns of agents' scores of the Short-term factor and Long-term balance factor are illustrated in fig.6.23a, 6.23b, and 6.23c. In the flat phase, the scores distributed in the minus are of the Short-term factor (fig.6.23a). In the bubble phase, they moved to the plus area (fig.6.23b and 6.23c). In the end of the bubble phase (fig.6.23c), they return to the center of x axis, and shifted to the minus area of the Long-term factor.

In fig.6.24, market averages of its component data are investigated. There

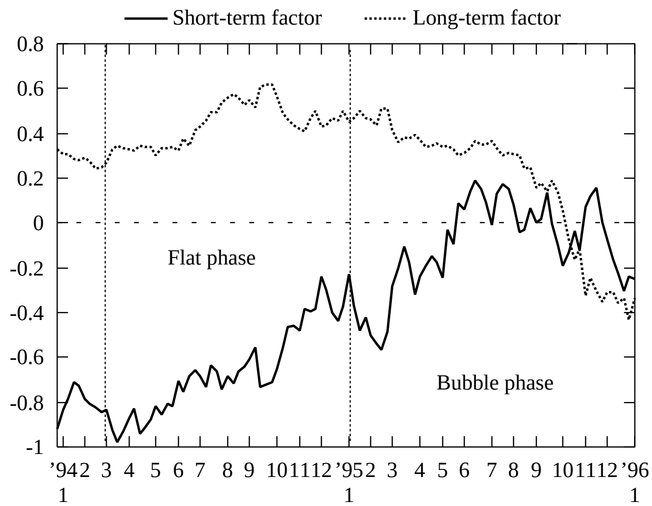


Figure 6.22: Means of trend factors

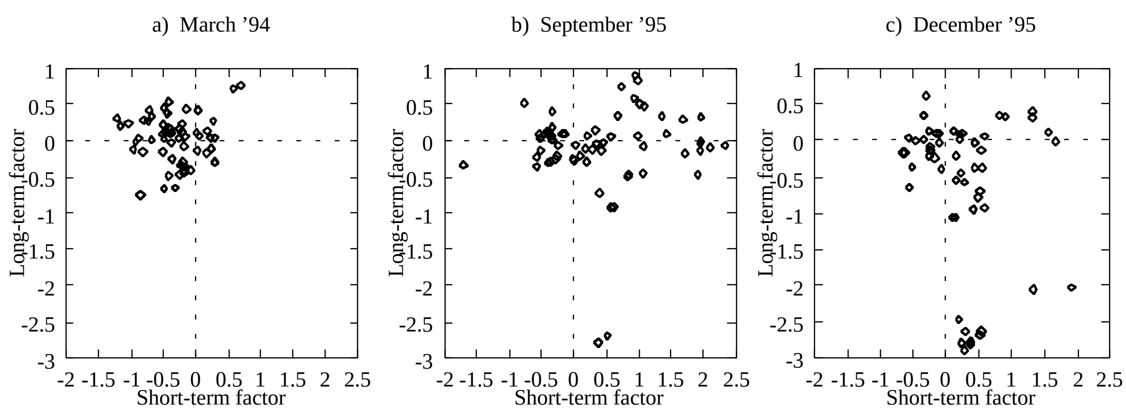


Figure 6.23: Scores of trend factors

is a slight increase of the weight of the Short-term data. From March 1995 to June 1995, there is an immediate sharp increase. Since July 1995 it returned. After the weight of the Long-term data moved flat from August 1994 to August 1995, it decreased rapidly. The point is that the weights of these two data are positive in the bubble phase. That is, there is a *positive feedback* by both the short-term and long-term trend in the bubble phase. The positive feedback means that the plus weights of trend data make the continuing trends. However in the end of the bubble phase, this positive feedback weakened because the weight of the Long-term data changed to the minus.

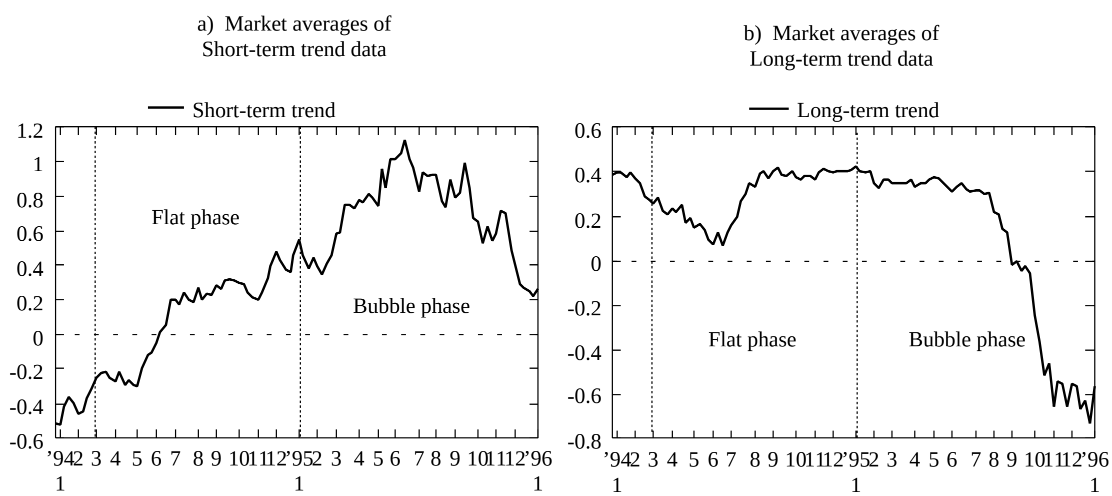


Figure 6.24: Market averages of component data of Trend category

We calculated the correlation coefficient between component data of the Trend category and rate changes from June 1994 to April 1995 and from May 1995 and December 1995 (table 6.11). Because of the large correlation before the bubble started, the weights of the trend data got larger, and the positive feedback started. However, after the rate passed the lowest point in

	Short-term	Long-term
June '94 − April '95	0.366	0.507
May '95 − December '95	0.034	−0.016

Table 6.11: Correlation coefficients between the Trend category and the rate change

May '95, the correlation coefficients became much smaller. It is because the lack of opposite order lead the forecasts made by the trend data to the failure as mentioned in section 6.3.1. Then, the positive feedback was weakened.

6.4.3 Mechanism of Phase Transition

Let us summarize the main points that have been made in the above sections concerning the phase transition of rate dynamics.

1. In the flat phase, the weights of the News and Trend categories are different among agents. In other words, there are variant opinions about these two categories. Hence, the variety of forecasts is rich. It leads to large trading amounts and small rate fluctuation. Opinions about the Econometrics category are stable and common in the market, but their influence is not so large in these period.

2. In the latter half of the flat phase, from summer in 1994, the Trade, Announcement, and Politics data appeared frequently. Then, many agents focused on these data because their correlation to the rate change is large.

3. Opinions about these data converged in the market. Moreover agents believed that the short-term and long-term trend would continue. This

beliefs made the trend further. Because of such positive feedback, the bubble phase started. In the bubble phase, the variety of forecasts is poor. It leads to small trading amounts and large rate fluctuation.

4. In May 1995, almost all forecasts in the market converged. Because there is no opposite order in the market, the downward trend vanished. Then the trend reversed and the bubble collapsed.

5. After the rate passed the lowest point in May 1995, the correlation coefficients between the trend data and the rate change became much smaller. Then, the weight of the Long-term data became negative, and the positive feedback was weakened. Finally the bubble phase ended.

6.5 Emergent Phenomena in Markets

In this section, based on the results in the section6.3 and 6.4, mechanisms of emergent phenomena in markets are investigated.

Many statistical studies and many dealers found that there are the following emergent phenomena in foreign exchange markets:

Rate bubbles Sometimes there are sudden large rises or falls of the rate, stops of such boosts, and sudden returns to the original level in markets. Such large fluctuations are defined as bubbles. Many bubbles cannot be explained only by economic fundamentals.

Departure from normality The distribution of rate changes is different from normal distribution [10, 18, 102, 103]. That is, exchange rate changes have peaked, long tailed (i.e. leptokurtsis) distributions. Moreover many statistical studies also reveal that exchange rate changes are not necessarily independent, identically distributed (iid) [10,81,82]. E-specially, there is indeed evidence of autocorrelation of rate variance.

Negative correlation between trading amounts and rate fluctuation There is negative correlation between trading volume and rate fluctuation [115,116]. Namely, when the rate fluctuates more, the volume is smaller. When the rate moves flat, the volume is larger.

Contrary Opinions Phenomenon Many dealers and their books say, " If almost all dealers have the same opinion, the contrary opinion will win." [59,115,116] In fact, survey data sometimes show that convergence of the dealers' forecasts leads to an unexpected result of the rate move.

The mechanism of rate bubbles is already discussed from the viewpoints of the bandwagon expectations (follow to the trends) and lack of opposite orders in the section6.3. In the following sections, we look at the mechanisms of the three emergent phenomena: departure from normality (section 6.5.1), negative correlation between trading amounts and rate fluctuation (section 6.5.2), and contrary opinions phenomena (section 6.5.3).

6.5.1 Departure from normality

The weekly rate changes in the real market from January 1994 to December 1995 have the peaked and fat tailed distributions (fig.6.25). The rate changes in the bubble group simulation also have the similar distributions to that of the actual rate changes. In fact, the kurtosis of the simulated rate changes is near that of the actual rate changes (table 6.12).

The mechanism of such leptokurtsis (peaked and fat tailed distributions) of rate changes can be explained by the idea, the phase transition. As shown

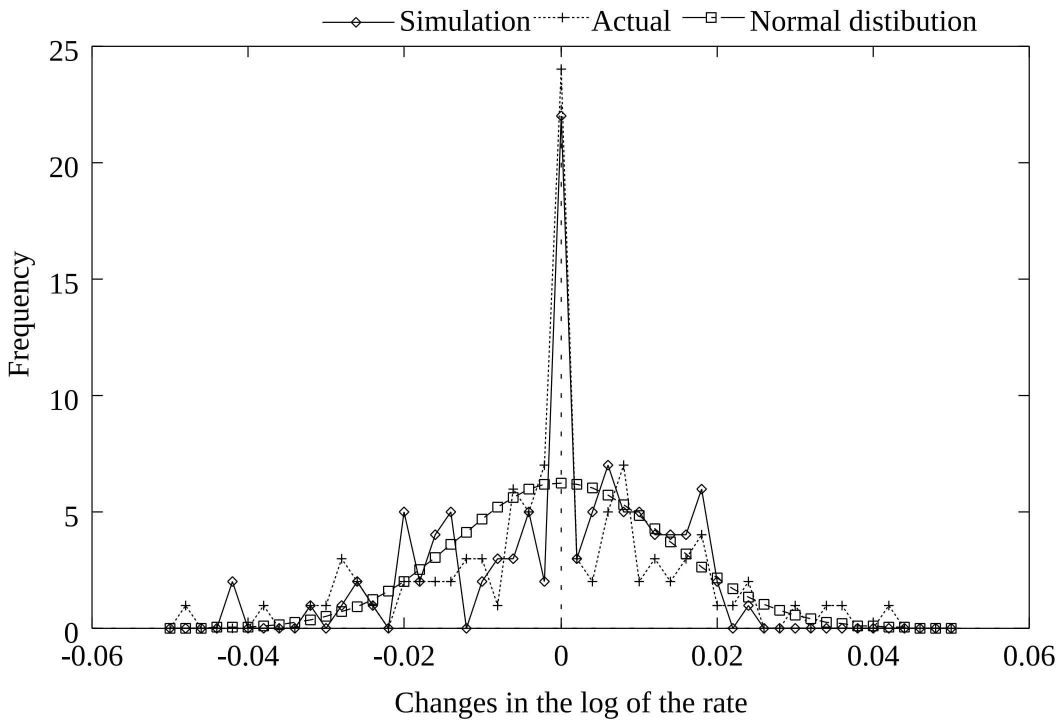


Figure 6.25: Distribution of rate change.

Actual rate changes	A typical simulated rate changes
0.564	0.477
(0.0 for normal distribution)	

Table 6.12: Kurtsis

table 6.5, the rate changes in the bubble phase are larger than those in the flat phase. Namely, the distribution of the rate changes in the bubble phase has a large variance, while that in the flat phase has a small variance. Because of the combination of these two distributions, the distribution of the rate changes during the whole periods is peaked and fat tailed (fig.6.26).

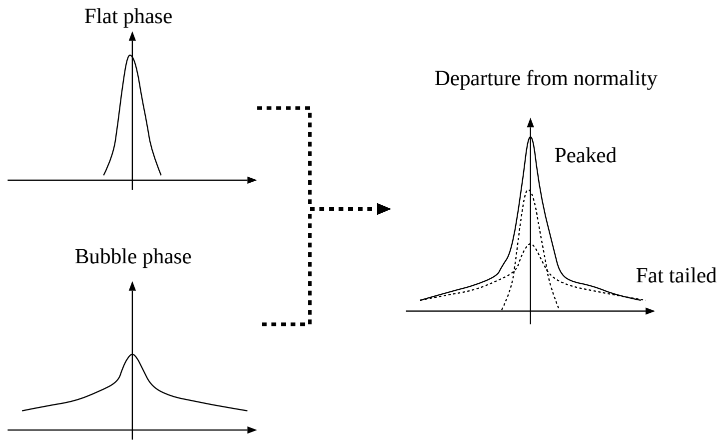


Figure 6.26: Mechanism of departure from normality

The mechanism of the autocorrelation of rate variance can be explained in the same way. In the bubble phase, large rate changes tend to be followed by large changes. In the flat phase, small changes tend to be followed by small changes. Hence, the rate variance shows the autocorrelation.

6.5.2 Volume and Fluctuation

For the typical simulation path mentioned above, we calculated the correlation between the absolute values of the rate fluctuation and the transaction amounts and obtained -0.2800. This shows that there is, significant negative correlation between the two.

This negative correlation is caused as follows: In the bubble phase, many (but not all) of the agents forecast changes in one direction, and the rate movement continues in that direction for many weeks. But the amount of transactions of exchanges gets small because the order quantity of the other direction are small. By contrast, in the flat phase, about a half of the agents forecast changes in one direction and the other half forecast changes in the other direction, the transaction amount will be larger.

6.5.3 Contrary Opinions Phenomenon

In May 1995, when almost all the agents' forecasts converge to the same forecast of the same direction, the rate will not move in that direction in the typical simulation path. As mentioned in the section 6.3.2, it is caused by the fact is that there are no order in the opposite direction and no transactions occur.

6.6 Comparison of the simulation results with the field data

In this section, the simulation results which have been said in section 6.3, 6.4, and 6.5, are compared with the field data. Then we discuss whether the model can simulate the real markets. The following three points are discussed:

- The 17 data weights were classified into three categories in section 6.4.2: Econometrics, News, and Trend category. Do dealers actually classify data in the same way?

- The dynamics of data weights from 1994 to 1994 were analyzed based on the simulation results in section 6.4.2. Is it realistic?
- The mechanism of emergent phenomena was explained in section 6.5. Do actual dealers observe the emergent phenomena in the real markets?

6.6.1 Classification of weights

In the same way that were mentioned in section 6.4.2, data weights which actual dealers answered in the surveys[6] are classified with factor analysis.

In the two surveys, dealers were asked questions about the following matters:

1. Weights of 25 factors in the recent trend.
2. Weights of 25 factors in the previous trend.
3. Weights of 25 factors in the future trend.

The 25 factors are economic activities, price, short-term interests, money supply, trade balance, employment, personal consumption, intervention, mark-dollar rates, commodities, stock, bonds, chart trends (1 week), chart trends (over 1 month), attitude of band of Japan, attitude of FRB, attitude of export and import firms, attitude of Insurance firms, attitude of securities firms, attitude of other banks, attitude of foreign investors, the other factor.

The matrix which is analyzed by factor analysis is a list of 25 weights of 12 (the first survey) + 10 (the second survey) dealers $\times$ 3 (the recent, previous, and future period). Thus, the width of matrix is 25, the height is 66.

[6] They are used in section 4.3. Questionnaires are shown in appendix B

We extracted 8 factors from the matrix with factor analysis (table 6.13).

	Factor 1	Factor 2	Factor 3	Factor 4
1	Commodities	FRB	Stock	Import firms
	0.8009	0.8394	0.8867	0.7085
2	Money supply	US government	Bond	Security firms
	0.7251	0.7778	0.8800	0.6920
3	Price	Bank of Japan	FRB	Export firms
	0.6363	0.6016	0.3707	0.6157
4	Employment	Japanese gov.	Japanese gov.	Japanese gov.
	0.6140	0.5196	0.3503	0.4625

	Factor 5	Factor 6	Factor 7	Factor 8
1	Other banks	Mark	Trend (1 week)	Trade balance
	0.6744	0.7158	0.6915	0.7162
2	Foreign investors	Economic activities	Trend (1 month)	Personal consumption
	0.6559	0.6956	0.5129	0.3181
3	Interest rates	Intervention	Bank of Japan	Employment
	0.5424	0.4060	0.3361	0.2997
4	Trend (1 week)	Trend (1 week)	Security firms	Japanese gov.
	0.4436	0.3026	0.2738	0.250

Four data with the largest loadings are shown.

Table 6.13: Loadings of factors

As a result, the factors can be clearly classified into the three categories: Econometrics, News, Trend categories. The factor 1, 3, 6, and 8 are included in the Econometrics category because they consist of econometric data. The factor 2, 4, and 5 are included in the News category because they consist of data about attitude of others. The factor 7 is included in the Trend categories because it consists of trend data.

In summary, the actual dealers also classify data in the same way as the simulation results.

6.6.2 Dynamics of weights

Each interviewee (the dealer X and Y) in section 4.2 ranked the factors in order of their weights (table 4.1 and 4.2). We compared temporal changes of the rank of factors in the interview data with the dynamics of weights in the computer simulation in section 6.4.2.

Econometrics category

Both in the computer simulation and the interview data of the dealer X, the weight of the trade balance factor was large in the first half of the bubble phase (the period VI and VII in the interview data). This supports the simulation results.

The other econometric factors were not mentioned in the interviews. Probably it is not necessary to bother to say about them because their interpretation is so common and fixed during these two years. If so, this fact is also similar to the simulation results.

News category

Both the dealer X and Y regarded the politics, intervention, and announcement factors as important during the bubble (the period VI, VII, and VIII of the dealer X and the period VI, V, and VII of the dealer Y). These interview data support the simulation results that market opinions about the news category converged in the bubble phase.

Trend category

Trend factors were not explicitly mentioned in the interviews. However both of the two dealers emphasized the importance of market sentiment (bullish or bearish) during the bubble. The market sentiment can be considered as a representation of market trend. Hence, their stress on the market sentiment supports the simulation results that the trend factors magnified rate fluctuation.

6.6.3 Emergent phenomena

The emergent phenomena, contrary opinions and negative correlation between trading volume and rate fluctuation, appeared also in the interview with the dealers. The interviews show that these phenomena are not designed directly in the agent level but become emergent in the market level. Hence, these phenomena are considered the emergent phenomena of the market.

Contrary opinions

In the period VII of dealer X (table 4.1), he missed the quick trend change until July 1995. He said, "Until July, almost all dealers didn't forecast the rate would return to the level of 100 yen by this year. It was unexpected." This is a good example of the contrary opinions. This interview data support the simulation results, in section 6.5.3, that the actual rate didn't move in that direction because almost all dealers' forecasts converged to the same forecast of one direction. In fact, the dealer X said, "According to my experience, when 90% or 95 % of all dealers have the same opinion, the rate reaches the peak."

Negative correlation

The interview data show that there is a negative correlation between the transaction amount and the width of the rate fluctuations. For example, in the period V of the dealer Y (table 4.2), he said that the trading volume was very small when the yen-dollar rate decreased quickly. He said, "There was sometimes no transaction when the rate moves quickly." This is consistent with the simulation results in the section 6.5.2.

Chapter 7

Discussion

In this chapter, we discuss the following matters:

- Difference from GA applications to other fields.
- Difference from previous multiagent models of markets.
- Comparison between the artificial market approach and rational expectations hypothesis.
- Relation to phase transition in physics.
- Difference from time-series models and Neural network models.

Difference from usual GA applications

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

Difference from previous multiagent models

There are two differences between this study and the previous multiagent models.

1. The previous studies mainly deal with the adaptation of the *Strategy Making* step but this study the *Prediction* step. The development of agents' mental models is corresponded to the adaptation of the Prediction step rather than Strategy Making step. Hence AGEDASI TOF has closer relations to the information process of actual agents in markets than the previous studies.

2. AGEDASI TOF uses the actual data series about economic fundamentals and political news. Previous studies use only trend factors. Therefore, AGEDASI TOF can investigate the actual rate dynamics not only qualitatively but also quantitatively.

Comparison with REH models

The most important difference between the artificial market approach and ration expectation hypotheses (REH) is the forecast variety.

REH assume that forecast mechanisms of all agents are essentially the same. That is, they prohibit the variety of agents' forecasts. The agents' forecasts distribute in only the normal distribution. However REH models can't explain any emergent properties in markets.

On the other hands, the artificial market approach permit agents' forecasts to be essentially different. The differences among agents' forecasts can be systematically correlated and interacted. Because of such forecast variety, this approach can explain the emergent properties which appear in the real markets: rate bubbles, rate change distributions depart from normality, contrary opinions, and Negative correlation between trading amounts and rate fluctuation.

Relation to phase transition in physics

Phase transition in the artificial market approach is similar to that in Ising models. The analogies are shown in table7.1.

Ising models (Spin glass)	Artificial markets
the direction of spins	the direction of forecasts
Force from mean fields	Chart trends
External force	Fundamentals
Ordered phase	Bubble phase
Non ordered phase	Flat phase
Temperature parameter	Distribution of weights

Table 7.1: Analogies between Ising model and artificial markets

Phase transition are very similar in these two systems. However there is one difference. The parameter is given externally in Ising model, while in the artificial markets the parameter is decided autonomously. Namely, the distribution of weights are decided by learning mechanism (GA operators) and rate determination mechanism (equilibrium). Hence, the phase transitions occur autonomously in the artificial markets.

Difference from time-series models and Neural network models.

Many studies found that there are some temporal characteristics of exchange rates as time-series data. Some of these characteristics are counterevidence to REH. According to these characteristics, some studies constructed time-series models of rate dynamics such as AR models, ARIMA models, and GARCH models. Although these time-series studies provide the evidence of such characteristics, they however provide little explanation about why these characteristics emerge.

Some market studies use neural network models. Their main purpose is to capture relevant inputs and to find optimal coefficients of the inputs. Namely they assume the existence of the *one static correct* relation between the inputs and outputs. Although they seek the *correct* relation, they don't explicitly describe why the relation exists, how it establishes, either whether it changes in the curse of time.

The point is that the aim of the artificial market approach is differ from that of time-series models and neural network models. The aim of time-series models and neural network models is to forecast the rate dynamics without explanation of economic structure or agents' interaction. Namely, they don't touch the mechanisms of emergence. By contrast, the aim of the artificial market approach is to simulate population dynamics of agents. This approach explains the mechanisms of emergence by economic structure or agents' interaction.

Chapter 8

Conclusions

This study is one of the first attempts to empirically test the multiagent features of a foreign exchange market. We proposed a new approach of foreign exchange market studies, an *artificial market approach*. The artificial market approach integrates fieldwork and multiagent models in order to explain the micro and macro relation in markets.

The artificial market approach has the three steps: observation in the field, construction of a multiagent model, and simulation of emergent phenomena in markets. The detailed description is as follows.

First, in order to investigate the learning patterns of actual dealers, we undertook both interviews and surveys. The interview data suggested that dealers replaced (a part of) his opinions about factors with other dealers' successful opinion when the forecasts based on his opinion were largely different from the actual rates. For justification of this hypothesis, we analyzed the survey data. The result showed that successful opinions which could forecast more accurately, spread in the market. That is, the hypothesis was supported also by the survey data. Based on these results, we discussed some analogies between the population dynamics in biology and the dynamics of dealers' opinions.

Second, we constructed a multiagent model of a foreign exchange market (AGEDASI TOF). On the basis of the result of the analysis of the field data, the interaction of agents' learning was described with genetic algorithms in our model. Compared with previous multiagent models, our model has two main features. First, our model incorporates the results of the analysis of the field data about dealers' learning. Next, our model can be applied to the quantitative analysis of the actual rate dynamics.

Finally, the emergent phenomena at the market level were analyzed using the simulation results of the model. The emergent phenomena which were analyzed in this study were rate bubbles, contrary opinions, rate change distribution apart from normality, and negative correlation between trading amounts and rate fluctuation.

Before the analysis of the emergent phenomena, our model was compared with a random walk model (RW) and a linear regression model (LR) in out-of-sample forecast tests in order to evaluate our model. The results of this comparison indicated that our model outperformed the other models over all forecast horizons.

The result of the analysis can be summarized as follows.

In order to analyze the rate bubbles, we generated out-of-sample forecast paths in two periods. The results of out-of-sample forecasts were found to be divided into two groups: the bubble group and the non-bubble group. First, we compared between the data weights in a typical case of the bubble group and those in a typical case of the non-bubble group. It was indicated that the agents in the bubble case were more sensitive to the fundamentals factors than in the non-bubble case. Next, we investigated supply and demand curves and dealing quantity around the collapse in the bubble case. It was found that just before the collapse dealing quantity was almost zero and that supply and demand relation was reversed in the collapses. As a result, we concluded that the bubble was triggered mainly by the external factors such as economic fundamentals and political news, grew as a result of the bandwagon expectations (positive feedback of trends), stopped growing by convergence of all agents' forecasts, and collapsed because of the change in the chart trend and the bandwagon expectations.

In order to analyze the other emergent phenomena, the phase transition of agents' forecast variety in the simulated paths was examined. Each simulated path was divided into two phases: highly fluctuated periods (bubble phases) and low fluctuated periods (flat phases). In the flat phase, a large variety of forecasts lead to large trading amounts and small rate fluctuation. By contrast, in the bubble phase, a small variety of forecasts lead to small trading amounts and large rate fluctuation. Then we classified the factors into the three categories: Econometrics, News, and Trend category. We investigated the dynamics of agents' opinions about each category. As a result, the following mechanism of the phase transition was proposed: convergence of opinions about news factors and trade factors, and positive feedback by trend factors caused phase transition from the flat phase to the bubble phase.

Based on the concept of the phase transition of forecast variety, we explained the three emergent phenomena. Flat tailed and peaked distribution of rate changes was explained by the combination of flat tailed distribution in the bubble phase and peaked distribution in the flat phase. Negative correlation between trading volume and rate fluctuation was explained by the their negative relation in two phases. The contrary opinions phenomenon was explained by the lack of opposite orders.

The results were, moreover, compared with the field data of the interviews and questionnaires in the three points: classification of factors, dynamics of weights, and mechanisms of emergent phenomena. As a result, the field data supported the simulation results.

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

Appendix A

Simple Genetic Algorithm

As shown by its name, the fundamental ideas of genetic algorithm come from population genetics. Genetic algorithms works with a population of symbols that in structure resemble chromosome. Each chromosome represents a potential solution for the problem under investigation or a decision rule for the decision making problem and so on.

Each chromosome has *fitness* value: it is defined as an index of how “good” this chromosome is. Calculation of fitness depends on the kind of the problems under investigation.

The individual strings within the population are gradually transformed using biologically based operations:*selection, crossover,* and *mutation*.

At each generation, genetic algorithm applies the calculation of the fitness and the three operators, and obtains a new population. Thus, a population of chromosomes “evolves”.

Selection

Selection makes the copies of individual chromosomes(Fig A.1). The criterion used in copying is the fitness values. Chromosomes with higher fitness value have a higher probability of contributing an offspring in the next generation. In this way, a percentage of the chromosomes is replaced by the copies. This percentage is called as a *generation gap*. And the rest chromosomes are left. Hence, selection works with $N \times G$ chromosomes, where N is the total number of chromosomes and G the generation gap.

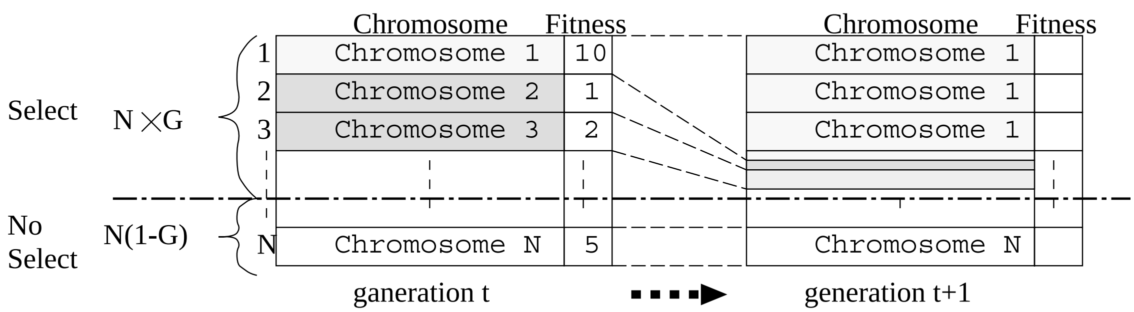


Figure A.1: Selection

Crossover

Crossover exchanges the pairs of randomly chosen strings(Fig A.2). It has two stages. First, we choose two strings randomly from the population. Second, we randomly choose a number of a splicing point k and form two new strings by swapping all symbols between the splicing point and the end of the strings. The total of $\frac{N \times G}{2}$ pairs are chosen and the crossover is performed on each pair with probability *pcross*.

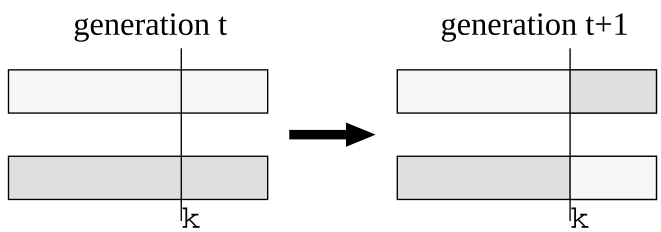


Figure A.2: Crossover

Mutation

Mutation randomly changes the value of a position within a string with a small probability *pmut* (FigA.3).

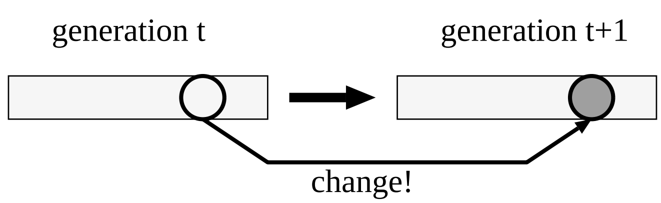


Figure A.3: Mutation

Appendix B

Questionnaires

The first survey

Day: March 1997

Respondents: 12 Dealers who usually deal with exchange markets in a bank.

Questionnaire: [1]

Name (   ) Date (   )

We would like to ask you about weekly trends in yen-dollar exchange rates. Please check or write your answers.

1. When did you recognize that the market trend changed to the yen down trend to 120 yen level?

   (   )

[1] Original sheets are written in Japanese.

2. What things had you recognize the yen down trend? Please check the answers from (a) to (g). Then please answer the subquestions.

   (a) Talks with other dealers.

   → What topics did you talk about?

   1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others (   )

   (b) Talks with your customers.

   → What topics did you talk about?

   1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others (   )

   (c) Orders which you received or infirmation about orders which brokers received.

   → Whose and what order?

   (   )

   (d) Level of the rate or signals from chart analysis.

   → (   ) yen → What signals? (   )

   (e) Reports or news letters of economists or mass media.

   → What were their topics?

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others (   )

(f) Announcements of VIP.

→ What were their topics?

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others (   )

(g) Economic indexes.

→ What indexes.

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds

3. What trend did you think the market was in, before the day which you answered in question 1?

   Until (   ) or to the level of (   ) yen,

   a. yen up trend. b. slighter yen down trend. c. sideway d. the others (   )

4. Please let us know your thoughts about other participants' order, their influence on the market, and factors which they watch in this yen down trend. Please check your answer from {Sell of dollar, buy, nothing} about their orders, check the levels from 0 to 10 about their influence, and check the answers from the following 15 matters about their factors.

(Example)

	Order of dollar	Infulence
		None Strongest
Economists	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

	Order of dollar	Infulence
		None Strongest
Japanese goverment	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

Order of dollar Infulence

None Strongest

US goverment {Sell, buy, nothing} 0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

Order of dollar Infulence

None Strongest

Export & import companies {Sell, buy, nothing} 0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

Order of dollar Infulence

None Strongest

Japanese institutinal investors {Sell, buy, nothing} 0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock

12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

	Order of dollar	Infulence
		None Strongest
Foreign invetors	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

	Order of dollar	Infulence
		None Strongest
The others ( )	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

5. When and at what level will the recent yen down trend end? What trend will the market enter after that?

   Until ( ) and to the level of ( ) yen the yen down trend will continue, then the market will market change to

a. yen up trend. b. slighter yen down trend. c. sideway d. the others ( ).

6. How important do you think the following factors are in the recent yen down trend, in the previous trend which you answered in question 3, and in the future trend which you answered in question 5? Please check from 0 to 10.

	the previous trend	the recent yen down trend	the future trend
	None Most important	None Most important	None Most important
Economic activities	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Price	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Short-term interests	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Money supply	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Trade balance	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Employment	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Personal consumption	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Intervention	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Mark-dollar rates	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Commodities	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Stock	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Bonds	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Chart trends (1 week)	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Chart trends (over 1 month)	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Band of Japan	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
FRB	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Ex(im)port firms	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Insurance firms	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Securities firms	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Other banks	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Foreign investors	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
The other ( )	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10

The second survey

Day: July 1997

Respondents: 10 Dealers who usually deal with exchange markets in a bank.

Questionnaire: [2]

Name ( ) Date ( )

We would like to ask you about weekly trends in yen-dollar exchange rates. Please check or write your answers. If nessesary, you can look at the attached data.

1. Since the yen-dollar rates reached at 127 yen, the market is in the yen up trend recently. When did you recognize that the market trend changed to such a yen up trend?

   ( )

2. What things had you recognize the yen up trend? Please check the answers from (a) to (g). Then please answer the subquestions.

   (a) Talks with other dealers.

   → What topics did you talk about?

   1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

[2] Original sheets are written in Japanese. A Chart graph of yen-dollar rates from April 1997 to June 1997 and lists of news headers were attached.

(b) Talks with your customers.

→ What topics did you talk about?

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

(c) Orders which you received or infirmation about orders which brokers received.

→ Whose and what order?

( )

(d) Level of the rate or signals from chart analysis.

→ ( ) yen → What signals? ( )

(e) Reports or news letters of economists or mass media.

→ What were their topics?

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

(f) Announcements of VIP.

→ What were their topics?

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity

markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others (   )

(g) Economic indexes.

→ What indexes.

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds

3. What trend did you think the market was in, before the day which you answered in question 1?

   Until (   ) or to the level of (   ) yen,

   a. yen down trend. b. sideway c. the others (   )

4. Please let us know your thoughts about other participants' order, their influence on the market, and factors which they watch in this yen up trend. Please check your answer from {Sell of dollar, buy, nothing} about their orders, check the levels from 0 to 10 about their influence, and check the answers from the following 15 matters about their factors.

(Example)

Order of dollar Infulence

None Strongest

Economists {Sell, buy, nothing} 0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

Order of dollar Infulence

None Strongest

Japanese goverment {Sell, buy, nothing} 0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

Order of dollar Infulence

None Strongest

US goverment {Sell, buy, nothing} 0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock

12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

	Order of dollar	Infulence
		None Strongest
Export & import companies	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

	Order of dollar	Infulence
		None Strongest
Japanese institutinal investors	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

	Order of dollar	Infulence
		None Strongest
Foreign invetors	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8.

Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

	Order of dollar	Infulence
		None Strongest
The others ( )	{Sell, buy, nothing}	0-+-+-+-+-5-+-+-+-+-10

→ Thier factors

1. Economic activities 2. Price 3. Short-tern interesr rates 4. Money supply 5. Trade balance 6. Employment 7. Personal consumption 8. Intervention 9. Mark-dollar rates 10. Commodity markets 11. Stock 12. Bonds 13. Chart analysis 14. Order from others 15. The others ( )

5. When and at what level will the recent yen up trend end? What trend will the market enter after that?

   Until ( ) and to the level of ( ) yen the yen down trend will continue, then the market will market change to

   a. yen down trend. b. sideway c. the others ( ).

6. How important do you think the following factors are in the recent from May to now, in the previous trend, and in the future trend which you answered in question 5? Please check from 0 to 10.

	Before May the previous trend	From May to now the recent yen down trend	From now the future trend
	None Most important	None Most important	None Most important
Economic activities	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Price	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Short-term interests	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Money supply	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Trade balance	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Employment	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Personal consumption	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Intervention	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Mark-dollar rates	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Commodities	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Stock	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Bonds	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Chart trends (1 week)	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Chart trends (over 1 month)	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Band of Japan	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
FRB	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Ex(im)port firms	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Insurance firms	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Securities firms	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Other banks	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
Foreign investors	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10
The other ( )	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10	0-+-+-+-+-5-+-+-+-+-10

Acknowledgments

I would like to acknowledge the continuing guidance and encouragement of Prof. Takashi Okatsu.

I wish to express a gratitude to Kazuhiro Ueda Ph.D, Mr Akihiro Nakanishi, Mr. Takuya Kojima, and Mr. Takashi Takabatake for helpful comments and encouragement.

My special thanks are due to many dealers who answered the survey. Especially, I would like to thank Mr. Yoshikazu Hamaie and Mr. Shingo Funatsuki for helpful suggestions.

I wish to thank Ms. Hiromi Yokoyama for reading the draft and making a number of helpful suggestions.

Thanks are due to my many colleagues with whom I have discussed several points in this paper.

Bibliography

[1] Andrew B. Abel and Frederic S. Mishkin. On the economic testing of rationality-market efficiency. *Review of Economics and Statics*, 63:318–323, 1983.

[2] Helen Allen and Mark P. Taylor. Charts, noise and fundamentals in the london foreign exchange market. *The Economic Journal*, 100:49–59, 1990.

[3] Martin Andrews and Richard Prager. Genetic programming for the acquisition of double auction market strategies. In Peter J. Angeline and Kenneth F. Kinnear, editors, *Advances in Genetic Programming*, pages 355–368. The MIT Press, 1994.

[4] Jasmina Arifovic. Genetic algorithm learning and the cobweb model. *Journal of Economic Dynamics and Control*, 18:3–28, 1994.

[5] Jasmina Arifovic. The behavior of the exchange rate in the genetic algorithm and experimental economies. *Journal of Political Economy*, 104(3):510–541, 1996.

[6] W. Brian Arthur. Designing economic agents that act like human agents: A behavioral approach to bounded rationality. *the American*

Economic Review, 81(2):353–359, 1991.

[7] W. Brian Arthur. Complexity in economic and financial markets. *Complexity*, pages 20–25, 1995.

[8] W. Brian Author, john H. Holland, Blake LeBaron, Richard Palmer, and Paul Tayler. Asset pricing under endogenous expectations in an artificial stock market. Technical report, Santa Fe Insititute, 1996.

[9] Richard T. Baille and Tim Bollerslev. Common stochastic trends in a system of exchange rates. *the Journal of Finance*, 44(1):167–181, 1989.

[10] Richard T. Baillie and Patrick C. McMahon. *The foreign exchange market: theory and economic evidence*. Cambridge University Press, Cambridge, 1989.

[11] Richard T. Baillie and David D. Selover. Cointegration and models of exchange rate determination. *International Journal of Forecasting*, 3:43–51, 1987.

[12] Fuji Bank. *Kinri Souba ga Wakaru Hon (in Japanese)*. Toyokan Shuppan Sha, Tokyo, 1991.

[13] Richard J. Bauer. Genetic algorithms and the management of exchange rate risk. In Jorg Biether and Volker Nissen, editors, *Evolutionay Algorithms in Management Applications*, pages 253–263. Springer Verlag, 1995.

[14] Andrea Beltratti and Sergio Margarita. Evolution of trading among heterogenous artificial economic agents. In Jean-Aready Meyer, Her-

berd L. Poitblat, and Stewert W. Willson, editors, *From Animals to Animats 2*, pages 494–501. The MIT Press, 1993.

[15] Hendrik Bessembinder. Bid-ask spreads in the interbank foreign exchange merkets. *Journal of Financial Economics*, 35:317–348, 1994.

[16] Lawrence Blume and David Easley. Evolution and market behavior. *Journal of Economic Theory*, 58:9–40, 1992.

[17] Edward J. Bomhoff and Pieter Korteweg. Exchange rate variability and monetary policy under rational expectations. *Journal of Monetary Economics*, 11:169–206, 1983.

[18] Paul Boothe and Debra Glassman. The statistical distribution of exchange rates: Empirical evidence and economic implications. *Journal of International Economics*, 2:297–319, 1987.

[19] James M. Boughton. Tests of the performance of reduced-form exchange rate models. *Journal of International Economics*, 23:41–56, 1987.

[20] M. M. Bray and N. E. Savin. Rational expectations equilibra, learning, and model specification. *Econometrica*, 54(5):1129–1160, 1986.

[21] Margaret Bray. Leanring, estimation, and the stability of rational expectations. *Journal of Economic Theory*, 26:318–339, 1982.

[22] Wiiliam A. Brock, David A. Hsieh, and Blake LeBaron. *Nonliner Dynamics, Chaos, and Instability: Stastistical Theory and Economic Evidence*. The MIT Press, 1991.

[23] Fabio Canova. Modeling and forecasting exchange rates with a bayesian time-varying coefficient model. *Journal of Economic Dynamics and Control*, 17:233–261, 1993.

[24] Fabio Canova and Jane Marrinan. Profits, risk, and uncertainty in foreign exchange markets. *Journal of Monetary Economics*, 32:259–286, 1993.

[25] José Castro and Helder Coelho. Strategic interaction in oligopolistic markets: Experomenting with real and artificial agents. In Cristiano Castelfranchi and Eric Werner, editors, *Artificial Social Systems*, pages 147–163. Springer Verlag, 1994.

[26] CECOIA IV Conference. *A Simulation of a Foreign Exchange Market using Genetic Algorithm: Quantitative Comparison with Other Models*, 1995.

[27] Rodolphe Chatagny and Bastien Chopard. Parallel simulation of a foreign echange market model. In *Proccedings of HPCN 97, Viena*. HPCN 97, 1997.

[28] Shu-Heng Chen and Chia-Hsuan Yeh. Toward a computable approach th the efficient market hypothesis: An application of genetic programming. From Internet.

[29] Shu-Heng Chen and Chia-Hsuan Yeh. Genetic programming and the efficient market hypothesis. In John R. Koza, David E. Goldberg, and David B. Fogel, editors, *Genetic Programming: Proceedings of the 1st Annual Conference*, pages 45–53. the MIT Press, 1996.

[30] Shu-Heng Chen and Chia-Hsuan Yeh. Genetic programming learning and the cobweb model. In Peter J. Angeline and Kenneth F. Kinnear, editors, *Advances in Genetic Programming 2*, pages 443–466. The MIT Press, 1996.

[31] Bastien Chopard and Rodolphe Chatagny. Models of artificial foreign exchange markets. In *Proccedings of Les Houches School on "Scale Invarience and Beyond"*. Les Houches School, 1997.

[32] Bradford Cornell. Spot rates, foraward rates and exchange market efficiency. *Journal of Financial Economics*, 5:55–65, 1977.

[33] Douglas D. Davis and Charles A. Holt. *Experimental Economics*. Princeton University Press, Princeton, 1992.

[34] Herbert Dawid. On the convergence of genetic learning in a double auction market. From Internet.

[35] Richard Dawkins. *The Selfish Gene: New Edition*. Oxford University Press, 1989.

[36] Michael de la Maza and Deniz Yuret. A futures market simulation with non-rational participants. In Rodney A. Brooks and Pattie Maes, editors, *Artificial Life IV*, pages 325–330. The MIT Press, 1994.

[37] Francis X. Diebold and James A. Nason. Nonparametric exchange rate prediction? *Journal of International Economics*, 28:315–332, 1990.

[38] Kathryn M. Dominguez. Are foreign exchange forecasts rational?: New evidence from survey data. *Economic Letters*, 21:277–281, 1986.

[39] Rudiger Dornbusch and Stanley Fischer. Exchange rates and teh current account. *the American Economic Review*, 70:960–971, 1980.

[40] Econometric Society. *An Analysis of an Exchange Rate Bubble with a Computer Simulation*, 1995.

[41] Sebastian Edwards. Exchange rates and 'news': A muliti-currency approach. *Journal of International Money and Finance*, 1:211–224, 1982.

[42] Sebastian Edwards. Floating exchange rates, expectations and new information. *Journal of Monetary Economics*, 11:321–336, 1983.

[43] Joshua M. Epstein and Robert Axtell. *Growing Artificial Societies*. The MIT Press, 1996.

[44] Robert Forsythe, Thomas R. Palfrey, and Charles R. Plott. Asset valuation in an experimental market. *Econometrica*, 50:537–567, 1982.

[45] Jeffrey A. Frankel and Kenneth A. Froot. Short-term and long-term expectations of the yen/dollar exchange rate: Evidence from survey data. *Journal of the Japanese and International Economics*, 1(3):249–274, 1987.

[46] Jeffrey A. Frankel and Kenneth A. Froot. Using survey data to test standard propositions regarding exchange rate expectations. *The American Economic Review*, 77(1):133–153, 1987.

[47] Jeffrey A. Frankel and Kenneth A. Froot. Chartists, fundamentalist, and trading in the foreign exchange market. *the American Economics Review*, 80(2):181–185, 1990.

[48] Jeffrey A. Frankel and Kenneth A. Froot. Chartists, fundamentalists and the demand for dollars. In A. Courakis and M. Taylor, editors, *Private Behavior and Goverment Policy in Interdependent economics*, pages 73–126. Oxford University Press, 1990.

[49] Jacob A. Frenkel. Flexible exchange rates, prices, and the role of news: Lessens from the 1970s. *Journal of Political Economy*, 89(4):665–705, 1981.

[50] Daniel Friedman and John Rust. *The Double Auction Market: Institutions, Theories, and Evidence*. Addison-Wesley, Reading, 1993.

[51] Kenneth A. Froot and Takatoshi Ito. On the consistency of short-run and long-run exchange rate expectations. *Journal of International and Finance*, 8:487–510, 1989.

[52] Kyoji Fukao. Kawase rate no kettei youin to kawase touki jyuyou (in japanese). *Kinyuu Kenkyuu*, 2:27–65, 1983.

[53] Domenico Delli Gatti, Mauro Gallegati, and Antonio Palestrini. Agents heterogenety, financial fragility and learning. From Internet.

[54] Nigel Gilbert and Jim Doran. *Simulating Societies*. UCL Press, 1994.

[55] Dhanajay K. Gode and Shyam Sunder. Human and artificially intelligent traders in computer double auctions. In Kathleen M. Carley and Michael J. Prietula, editors, *Computational Organization Theory*, pages 241–262. Lawrence Erlbaum Associates, Publishers, 1994.

[56] David E. Goldberg. *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley Publishing Company, 1989.

[57] Charles Goodhart, Takatoshi Ito, and Richard Payne. One day in june 1993: A study of the working of the reuters 2000-2 electronic foreign exchange trading system. In Jeffery A. Frankel, Giampaolo Galli, and Alberto Giovannini, editors, *The Microstructure of Foreign Exchange Markets*, pages 107–182. National Bureau of Economic Research, 1996.

[58] Paul De Grauwe, Hance Dewachter, and Mark Embrechts. *Exchange Rate Theory: Chaotic Models of Foreign Exchange Markets*. Blaclwell, Oxford, 1993.

[59] Yasushi Hayashi. *Yen Dollar Souba no Hendou wo Yomu (in Japanese)*. Toyo Keizai Shinpo Sha, Tokyo, 1991.

[60] Yasushi Hayashi. *Souba to shiteno Gaikoku Kawase (in Japanese)*. Toyo Keizai Shinpo Sha, 1993.

[61] Geoffrey M. Hodgson. *Economics and Evolution: Bringing Life Back into Economics*. Polity Press, Cambridge, 1993.

[62] J. H. Holland, K. J. Holyoak, R. E. Nisbett, and P. R. Thagard. *Induction: Process and Inference, Learning, and Discovery*. the MIT Press, Cambrige, 1986.

[63] John H. Holland. the global economy as an adaptive process. In Philip W. Anderson, Kenneth J. Arrow, and David Pines, editors, *The Economy as an Evolving Complex System*, pages 117–124. Addison-Wesley, 1988.

[64] John H. Holland and John H. Miller. Artificial adaptive agents in economic theory. In *American Economic Review:Papers and Proceedings*

of the 103rd Annual Meeting of the American Economic Association, pages 365–370, 1991.

[65] Nakazi Honda, Tomohoro Takagi, and et al. *Fuzzy Expert Systems.* Nikkan Kogyo Shinbun Sha, Tokyo, 1993.

[66] John P. Hussman. Market efficiency and inefficiency in rational expectations equilibria. *Journal of Economic Dynamics and Control*, 16:655–680, 1992.

[67] Selahattin İmrohoroğlu. Testing for sunspot equilibria in the german hyperinflation. *Journal of Economic Dynamics and Control*, 17:289–317, 1993.

[68] Takatoshi Ito. Foreign exchange rate expectations: Micro survey data. *the American Economic Review*, 80(3):434–449, 1990.

[69] Takatoshi Ito and V. Vance Roley. News from the u.s. and japan. *Journal of Monetary Economics*, 19:255–277, 1987.

[70] Gyoichi Iwata. Toukiteki kakaku hendo ni tsuiteno ichi shiron (in japanese). *Mita Shogaku Kenkyuu*, 32:143–159, 1989.

[71] Kiyoshi Izumi. Expectations formation and determination of exchange rates (in japanese). Graduate Thesis (University of Tokyo), 1993.

[72] Kiyoshi Izumi. A simulation of a foreign exchange market with genetic algorithm. Master's thesis, The University of Tokyo, 1995.

[73] Kiyoshi Izumi and Takashi Okatsu. An artificial market analysis of exchange rate dynamics. In Lawrence J. Fogel, Peter J. Angeline, and

Thomas Bäck, editors, *Evolutionary Programming V: Proceedings of the 5th Annual Conference on Evolutionary Programming*, pages 27–36. the MIT Press, 1996.

[74] Maarten C. W. Janssen. *Micro and Macro in Economics: An Inquiry into Their Relation*. Wolters-Noordhoff, Netherlands, 1990.

[75] Richard J. Bauer jr. *Genetic Algorithms and Investment Strategies*. John Wiley & Sons, New York, 1994.

[76] John H. Kagel and Alvin E. Roth. *The Handbook of Experimental Economics*. Princeton University Press, Princeton, 1995.

[77] John M. Keynes. *The General Theory of Employment, Interest and Money*. Macmillan, London, 1936.

[78] Robert G. King, Neil Wallace, and Warren E. Weber. Nonfundamental uncertainty and exchange rates. *Journal of International Economics*, 32:83–108, 1992.

[79] Hirao Kojima. *The Time Series Analysis of Rate Voriability (in Japanese)*. Makino Shoten, Tokyo, 1994.

[80] Paul A. Laux. Delaer market structure, outside competetion, and the bid-ask spread. *Journal of Economic Dynamics and Control*, 19:683–710, 1995.

[81] Richard K. Lyons. Tests of microstructual hypotheses in the foreign exchange market. *Journal of Financial Economics*, 39:312–351, 1995.

[82] Richard K. Lyons. Foreign exchange volume: Sound and fury signifying nothing? In Jeffery A. Frankel, Giampaolo Galli, and Alberto

Giovannini, editors, *The Microstructure of Foreign Exchange Markets*, pages 183–208. National Bureau of Economic Research, 1996.

[83] Ronald Macdonald. Some tests of the rational expectations hypothesis in the foreign exchange market. *Scottish Journal of Political Economy*, 30(3):235–250, 1983.

[84] Ronald MacDonald. *Floating Exchange Rates: Theories and Evidence.* Unwin Hyman, London, 1988.

[85] Ananth Madhavan and Seymour Smidt. A bayesian model of intraday specialist pricing. *Journal of Financial Economics*, 30:99–134, 1991.

[86] Ramon Marimon, Ellen McGrattan, and Thomas J. Sargent. Money as a medium of exchange in an economy with artificially intelligent agents. *Journal of Economic Dynamics and Control*, 14:329–374, 1990.

[87] Joram Mayshar. On divergence of opinion and imperfections in capital markets. *the American Economic Review*, 73:114–128, 1983.

[88] James W. McFarland, Richardson Pettit, and Sam K. Sung. The distribution of foreign exchange price changes: Trading day effects and risk meadurement. *the Journal of Finance*, 37:693–715, 1982.

[89] Richard Meese and Kenneth Rogoff. the out-of-sample failure of empirical exchange rate models: Sampling error or misspecification? In Jacob A. Frenkel, editor, *Exchange Rates and International Macroeconomics*, pages 67–112. The University of Chicago Press, 1983.

[90] Richard A. Meese. Testing for bubbles in exchange markets: A case of sparkling rates? *Journal of Political Economy*, 94(2):345–373, 1986.

[91] Richard A. Meese and Kenneth J. Singleton. On unit roots and the empirical modeling of exchange rates. *the Journal of Finance*, 37:1029–1035, 1982.

[92] Richrad A. Meese and Kenneth Rogoff. Empirical exchange rate models of the seventies. *Journal of International Economics*, 14:3–24, 1983.

[93] Paul Milgrom and Nancy Stokey. Information, trade and common knowlegde. *Journal of Economic Theory*, 26:17–27, 1982.

[94] John F. Muth. Rational expectations and the theory of price movements. *Econometrica*, 29(3):315–335, 1961.

[95] Christian Nottola, Frédéric Leroy, and Franck Davalo. Dyanmics of artificial markets. In F.J. Varela and P. Bpurgine, editors, *Toward a Practice of Autonomous Systems: Proceedings of the 1st European Conference on Artifical Life*, pages 185–194. The MIT Press, 1992.

[96] Maureen O'hara. *Market Microstructure Theory*. Blackwell Publishers Inc., Cambridge, 1995.

[97] Kunio Okina. *Touki to Kitai no Keizai Bunseki (in Japanese)*. Toyo Keizai shinpo Sha, Tokyo, 1985.

[98] R.G. Palmer, W.rian Arthur, John H. Holland, Blake LeBaron, and Paul Taylor. Artificial economic life:a simple model of a stock market. *Physica D*, 75:264–265, 1994.

[99] Eric J. Pentecost. *Exchange Rate Dynamics: A Modern Analysis of Exchange Rate Theory and Evidence*. Edward Elgar, Vermont, 1993.

[100] William Perraudin and Paolo Vitale. Interdealer trade and information flows in a decetralized foreign exchange market. In Jeffery A. Frankel, Giampaolo Galli, and Alberto Giovannini, editors, *The Microstructure of Foreign Exchange Markets*, pages 73–106. National Bureau of Economic Research, 1996.

[101] M. Hashem Pesaran. Consistency of short-term and long-term expectations. *Journal of International Money and Finance*, 8:511–516, 1989.

[102] Edger E. Peters. *Chaos and Order in the Capital Markets: A New view of Cycles, Prices, and Market Volatility.* John Willey & Sons, Inc., Canada, 1991.

[103] Edger E. Peters. *Fractal Market Analysis: Applying Chaos Theory to Investment and Economics.* John Willey & Sons, Inc., Canada, 1994.

[104] John Rust, John H. Miller, and Richard G. Palmer. Behavior of trading automata in a computerized double auction market. In Daniel Friedman and John Rust, editors, *The Double Auction market: Institutions, Theories, and Evidence*, pages 155–198. Addison-Wesley, 1993.

[105] John Rust, John H. Miller, and Richard G. Palmer. Characterizing effective trading strategies: Insights from a computerized double auction tournament. *Journal of Economic Dynamics and Control*, 18:61–96, 1994.

[106] Thomas J. Sargent. *Bounded Rationality in Macroeconomics.* Clarendon Press, Oxford, 1993.

[107] Robert Shiller. *Market Volatility.* The MIT Press, 1989.

[108] Kip C.S. Smith. *Decision Making in Rapidly Changing Enviroments: Trading in the Spot Currency Markets*. PhD thesis, University of Minnesota, 1996.

[109] Kip C.S. Smith. How currency traders think about the spot market's thinking. In *Proceedings of the 19th Annual Conference of the Cognitibe Science Society*, pages 703–708, 1997.

[110] Vernon L. Smith. *Papers in Experimental Economics*. Cambridge University Press, Cambridge, 1991.

[111] Vernon L. Smith, Gerry L. Suchnek, and Arlington W. Williams. Bubbles, clashes, and endogenous expectations in experimental spot asset markets. *Econometrica*, 56(5):1119–1151, 1988.

[112] Joachim Stender, Kifah Tout, and Peter Stender. Using genetic algorithms in economic modelling: The many-agents approach. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 607–612. Springer-Verlag, 1993.

[113] Shinji Takagi. Exchange rate expectations: A survey of survey studies. *IMF Staff Papers*, 38(1):156–183, 1991.

[114] Yukuo Takahashi. *a Foreign Exchange Guide Book by a Top Dealer/ Revised edition (in Japanese)*. Jiji Tsushin Sha, Tokyo, 1989.

[115] Taisuke Tanaka. *Souba ha Chiteki Kakutougi de Aru (in Japanese)*. Kodansha, Tokyo, 1991.

[116] Taisuke Tanaka. *Market ha Naze Machigaeru no ka (in Japanese)*. Toyo Keizai Shinpo Sha, Tokyo, 1995.

[117] Jean Tirole. On the possibility of speculation under rational expectations. *Econometrica*, 50:1163–1181, 1982.

[118] The Sumitomo Trust and Ltd Banking Co. *Kinri Kawase Yosoku Handbook (in Japanese)*. Nihon Hoso Shuppan Kyokai, Tokyo, 1994.

[119] Andres S. Weigend, Bernard A. Huberman, and David E. Rumelhart. Predicting sunspots and exchange rates with connectionist networks. In Martini Casdagli and Stephan Eubanl, editors, *Nonlinear Modelling and Forecasting*, pages 395–432. Addson-Wesley, 1992.

[120] Janice Moulton Westerfield. An examination of foreign exchange risk under fixed and floating rate regimes. *Journal of International Economics*, 7:181–200, 1977.

[121] Arata Yaguchi. *Ikinokori no Dealing (in Japanese)*. Toyo Keizai Shinpo Sha, Tokyo, 1990.

[122] Hiroshi Yoshikawa. On the equilibrium yen-dollar rate. *the American Economics Review*, 80:576–583, 1990.

[123] H. Yuize, T. Yagyu, M. Yoneda, Y. Katoh, S. Tano, M. Grabisch, and S. Fukami. Foreign exchange trade support expert system. In *Proceedings of IFSA '91 Brussels, Artificial Intellgence*, pages 214–217, 1991.