Learning Foreign Exchange Intervention Policies with an Artificial Market

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Abstract

We propose a multi-agent system which learns intervention policies and evaluates the effect of interventions in an artificial foreign exchange market. We introduce an intervention agent that has the role of the central bank to stabilize the market. We could show that the agent learned the effective intervention policies through the reinforcement learning.

Keywords: artificial market, multi-agent system, foreign exchange market, reinforcement learning, complex system

1 Introduction

It is difficult for us to predict how foreign exchange rates change. It is also difficult for governments which can intervene in the market with massive funds to predict and control them. In fact, the dollar-yen rate was not stable, keeping dollars rather high, though the Japanese government intervened and bought dollars for 20 trillions of yen through 2003 [6]. Why cannot the governments control the rate completely? How do those interventions affect the rate?

We propose a multi-agent system which learns intervention policies and evaluates their effects in an artificial foreign exchange market. Our purpose is to analyze the effect of interventions and to learn control mechanisms by using it.

In this paper, we introduce our artificial market model in Section 2. Then we incorporate an intervention agent which has the role of the government in an actual market into our artificial market model in Section 3. In Section 4, we present the results of experimentations, and conclude in Section 5.

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2 Artificial Market Model

Our artificial foreign exchange market model is a multi-agent model with 100 dealer agents, and it is based on AGEDASI TOF[1] [3]. The agents supposed to be foreign exchange dealers, which have dollar and yen assets and deal the currencies for the purpose of making profits.

The system iteratively executes the following five steps for a week using weekly data in Tokyo foreign exchange market (Fig. 1).

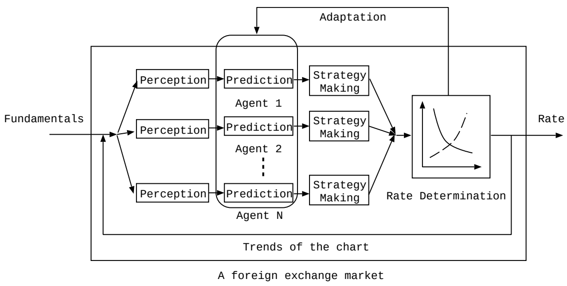

Fig. 1. Framework of our artificial market model.

In **Perception** step, agents receive 17 *factors*[2] affecting the dollar-yen rate. For such a factor, $x^k(t)$ is defined as a value to express the impact of news of the kind k at the beginning of week t.

After perception, in **Prediction** step, agents predict future changes of the rate with their own weights $w_i^k(t)$ for 17 factors $x^k(t)$. $w_i^k(t)$ is a weight of each news k in each agent i's prediction of the future rate at week t.

[1]A GEnetic-algorithmic Double Auction SImuration in TOkyo Foreign exchange market

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

In **Strategy Making** step, agents decide their trading strategy (to buy or sell dollars) in order to maximize their profits on the basis of their prediction.

After the submission of orders, in **Rate Determination** step, the exchange rate in this week is fixed at the equilibrium rate where amount of demand and that of supply are balanced.

Different agents have different prediction methods (combinations of the weights $w_i^k(t)$). After the rate determination, agents revise their prediction methods using other agents' predictions in **Adaption** step.

The system starts with agents whose initial weights are randomly given. During the first dozens of weeks (*training period*), it omits the rate determination step and uses the actual rate data as training data. After the training period, it does not use actual rate data at all and determines the equilibrium rate artificially in the rate determination step (*test period*). See our preceding study [4] for details.

3 Intervention Agent

We incorporate an intervention agent which plays a role of the government in an actual market into our artificial market model. In the foreign exchange market, it is supposed that interventions affect the rate through two channels: the portfolio balance channel[3] and the signaling channel.[4] It is reported that the effect through the signaling channel is larger than that through the portfolio balance channel [1, 7]. In this study, we define signaling effect as the influence of signaling by the intervention agent on the rate, we try to examine how effective is the signaling by comparing the experimental results of interventions with and without signaling. Additionally, considering that the government cannot know all about the market each dealer's prediction, order amount, and so on, we try to answer how well it can control the rate by interventions. In order to this, we equipped the intervention agent with a reinforcement learning feature to get effective intervention policies.

The intervention agent is different from dealer agents in the following points.

Mission: Stabilizing the rate in the target range.[5]

Actions in each step:

In Strategy Making step, the agent decides intervention amounts. In the case of intervention with signaling, the actions are perceived by dealers with the factor about intervention amount ($x^8(t)$).

In Adaptation step, the agent acquires effective intervention policies with a reinforcement learning.

3.1 Finding Effective Intervention Policies

The purpose of the intervention agent is to find effective intervention policies to stabilize the rate by a reinforcement learning, Profit Sharing [2]. The method reinforces weights of rules on episodes[6] to get rewards without bootstrapping, where a rule is a set of a state **S** and an action a which can be selected at the state. We show the definitions of states **S**, actions a, and the way to reinforce weights $W(\mathbf{S}, a)$.

State In this study, we define a state **S**, that is a situation of a market as well as a state of learning, as a tuple as follows:

$$\mathbf{S} \equiv \left(\bar{E}, \sigma_E, \overline{w^8}, \sigma_{w^8}, x^{15}, R\right), \tag{1}$$

where $\bar{E}$ denotes the average predicted rate of dealer agents and σ_E denotes its standard deviation. $\overline{w^8}$ and σ_{w^8} denote dealer agents' average weight of intervention and its standard deviation, and x^{15} denotes the short-term trend. R denotes the exchange rate. Each member of a state takes a numeric value from 5 to 11. We postulated finer-grained grading for R than our previous study [5], to observe the rate fluctuation closely.

Action An action a is a normalized intervention amount as follows:

$$a \equiv \frac{3q}{Q}, \tag{2}$$

where a ranges among seven discrete values $\{\pm 3, \pm 2, \pm 1, 0\}$, q denotes the intervention amount (the order amount), Q denotes the maximum amount of intervention in a week, and the order rate of the agent is kept at the median of the target range. In addition,

[3] Interventions affect the supply and the demand in the market, then they change the rate.

[4] The dealers notice the aim of the central bank through interventions and they change their predictions. Then they change the rate.

[5] Different from other dealer agents, the agent disregards profits.

[6] An episode is a sequence of selected rules.

the action of the intervention agent is perceived by dealer agents through $x^8(t)$. The agent selects actions according to the roulette wheel selection or the Boltzmann selection with the temperature $\tau = 1$.

Reward Weights of the rules $W(\mathbf{S}, a)$ are changed in the following four ways.

All: Estimation of the rates in the whole test period. Weights of all the rules[7] on the episode are increased by r uniformly when the rates are stable (in the target range) in the whole test period.

Week: Estimation of the rate at each week. $W(\mathbf{S}, a)$ are changed with immediate rewards of these ways. The agent is not concerned with future rewards in the ways.

1. The weight is increased by $r/2$ if it comes near to the median of the target range.
2. The weight is decreased by $r/2$ if it deviates from the target range.
3. The weight is decreased by $r/2$ if the intervention agent does not execute exchanges though the agent ordered because they do not affect supply-demand at all. In cases, the agent ordered to buy (sell) dollars, but the decided rate is higher (lower) than the order rate.

In this study, the above rewards r are equal to one-tenth of the initial weights of rules.

4 Experiments with Intervention Agent

In this section, we evaluate the effect of the interventions by the proposed intervention agent.

4.1 Settings and Methods of Experiments

The dollar-yen rate dropped by about 20 yen for a week in October 1998. We employ the data of this year as the test period. We record 100 kinds of initial conditions of dealer agents at the first week of January 1998 at the initial stage. One initial condition of dealer agents is made by the 20 times' repetition of the training period between January 1996 and December 1997 with the actual rate and factors. Then, we repeat 200,000 times of simulations on the test period with the intervention agent and dealer agents. Prior to each simulation, the dealer agents are initialized by one of the recorded initial conditions by rotation. The intervention agent retains the weights of intervention rules after each simulation finishes.

Target Range of The Rate For simplicity, we presuppose that the target range of the rate is between 130.39 ± 10 yen, all through the experimentation period.[8]

Maximum intervention amount *Q* We plan several experiments as are shown in Table 1.

Table 1. Experiments on intervention amounts and signaling.

	Q	signaling
$(30\bar{q_a}$, yes)	$30\,\bar{q_a}$	yes
$(10\bar{q_a}$, yes)	$10\,\bar{q_a}$	yes
$(\bar{q_a}$, yes)	$\bar{q_a}$	yes
$(30\bar{q_a}$, no)	$30\,\bar{q_a}$	no
$(10\bar{q_a}$, no)	$10\,\bar{q_a}$	no
$(\bar{q_a}$, no)	$\bar{q_a}$	no

$\bar{q_a}$: the average amount of agents' orders at simulations without the intervention agent.

Evaluation Method We name a path the rate in which stays in the target range through the test period a *stable path*. We evaluate the experiments by the ratio of the appearance of stable paths (*stable ratio*).

4.2 Results of Experiments

We show the experimental results in Table 2. Those of learning intervention agents are compared with the data by the **Random** interventions and the hypothetical **Ideal** data. The random intervention means to select actions randomly from seven values (Eq. 2).[9] The ideal data are calculated with the best action in the

[7] The number of rules is equal to the number of weeks in the test period.

[8] The range is derived from the rate at the last week of 1997, which is 130.39 yen.

[9] The random intervention is not 'random order.' Neverthless at random, it is effective since order rates is fixed at the middle of the target range of the rate.

Table 2. The stable ratios by various types of interventions.

	Random	Profit Sharing with		Ideal
		RWS	BMS	
($30\bar{q_a}$, yes)	48.36 %	67.10 %	73.70 %	98.65 %
($10\bar{q_a}$, yes)	34.85 %	49.40 %	56.55 %	90.83 %
($\bar{q_a}$, yes)	20.63 %	35.45 %	45.90 %	78.64 %
($30\bar{q_a}$, no)	45.71 %	56.40 %	60.50 %	93.78 %
($10\bar{q_a}$, no)	29.20 %	41.75 %	45.75 %	80.80 %
($\bar{q_a}$, no)	17.36 %	31.50 %	37.50 %	49.46 %

RWS: Roulette Wheel Selection
BMS: Boltzmann Selection

seven values at each weak by all the perceivable values in the market.

We can interpret the results as follows. The interventions with larger amount and with signaling could make the rate more stable. It is natural that interventions with larger amount are more effective, though it is noteworthy that signaling is far effective. In order to understand the reason, we need further detailed analysis of dealer agents' weights of interventions.

In the meanwhile, the learning intervention agents could stabilize more effectively than random interventions, but less than that of the ideal case. The fact seemed to result from the perceptual aliasing problem and the concurrent learning problem. However, the stable ratios are rather higher than ones of our previous study [5]. It is due to the fine glanularities of the state description of the rate. In addition, as to how to select actions, the Boltzmann selection was better than the roulette wheel selection, as the former works greedily because of the low temperature. The concurrent learning problem seems not to appear so conspicuously because the influence of the interventions overcomes it, even so the intervention amount is small, in the situation of the market.

5 Conclusion

In this study, we proposed an artificial market model and incorporated the intervention agent into our model. Since the agent has an ability to learn effective intervention policies automatically, we can examine the availability of interventions in various situations by using the model.

We found that

- the signaling is essential,
- learning difficulty results from the perceptual aliasing problem and the concurrent learning problem, and
- the greedy selection of actions and the detailed state description are effective depending on conditions,

through the experiments.

In the future work, we need to analyze change of dealer agents' weights under interventions, and also to investigate the phenomina under finer-grained description of states, to clarify the influence of learning problems. Additionally, we need to let the intervention agent count the fluctuations in order to learning effective policies to stabilize the rate.

References

[1] Katharyn M. Dominguez and Jeffrey A. Frankel. *Does Foreign Exchange Intervention Work?* Institute for International Economics, Washington, DC, 1993.

[2] John J. Grefenstette. Credit assignment in rule discovery systems based on genetic algorithms. *Machine Learning*, **3**, 225–245, 1988.

[3] Kiyoshi Izumi and Kazuhiro Ueda. Analysis of exchange rate scenarios using an artificial market approach. In *Proceedings of the International Conference on Artificial Intelligence*, pp. 360–366. CSREA Press, 1999.

[4] Hiroki Matsui and Satoshi Tojo. Artificial market with intervention agent. In *Proceedings of the 1st Indian International Conference on Artificial Intelligence*, 2003.

[5] Hiroki Matsui and Satoshi Tojo. Analysis of foreign exchange interventions by intervention agent with an artificial market approach. *Journal of the Japanese Society for Artificial Intelligence*, **20**(1), pp. 36–45, 2005. (in Japanese).

[6] Ministry of Finance Japan. Foreign exchange intervention operations, 2001–2005. http://www.mof.go.jp/e1c021.htm.

[7] Ramana Ramaswamy and Hossein Samiei. The yen-dollar rate : Have interventions mattered? *IMF Working Paper*, 2000.