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Agent Heterogeneity and Facility Congestion

Shigeru Matsumoto[1, 2, 3], Taiyo Maeda[2, 3], Tadahiko Murata[2, 3, 4],
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Abstract

This paper extends the laboratory experiment of agent's choice behavior conducted by Selten et al. (2007). In our laboratory experiment, 8 subjects choose one of the two facilities that provide an identical service. We assume that the cost of using facilities depends on the congestion level of a chosen facility. We further assume that there are two types of agents with different costs: high and low-cost agents. We then examine whether cost difference affects the facility selection of the agent. Our experimental results demonstrate that cost heterogeneity does influence neither the facility selection of the agent nor the congestion level of the facilities. Using the data of laboratory experiment, we develop state-action tables and computationally simulate the facility selection of the subject. We find that the subject decides whether it remains in the same facility or moves to the other facility in the next period according to the current congestion level.

Keyword: Agent Heterogeneity, Congestion, Facility Choice, State-Action Table

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1. Introduction

The benefits and costs of public services are affected by congestion. For example, if many people are waiting in line at the postal office, we have to spend time until obtaining the postal service. Irrespective of time spent in line, we will obtain the same postal service. If many students are assigned to the single class, they have to take a lecture in a crowded classroom. Although the opportunity cost of taking a lecture is the same, the quality or benefit of educational service decreases as the number of students increases.

People often expect that the government will provide the same quality of service at all public facilities. For example, patients presume that they can access to the same health care at all public clinics. Parents hope that the same educational service is available at all public schools. In a wide variety of situations, the government cannot differentiate service quality among public facilities. This restriction makes the optimal allocation of facility users an important research agenda on the provision of the public services characterized by consumption externalities. [1]

Tiebout (1956) argues that individuals sort themselves in a way that provides the most desirable allocation of public goods. If the same service is available at all facilities, then a rational agent will move into a less crowded facility. Therefore, congestion problems of public facilities will be resolved through "voluntary sorting."

Three natural questions arise about voluntary sorting. The first question is whether or not the optimal user allocation is achieved through voluntary sorting as Tiebout predicted. The second question is the stability of the optimal user allocation. The last question is the mechanism that reduces the deviation from the optimal user allocation.

The existence and the nature of equilibria of voluntary sorting have been studied in the literature of club economies. Scotchmer and Wooders (1986) examine whether or not the major conclusion from the theory of competition in private-goods economies applies to "club economies" with "anonymous crowding."[2] They argue that consumers' demand for facility size and crowding must be similar in each club when consumers are grouped into the approximate core. Milchtaich (1996) analyzes voluntary sorting as a class of noncooperative crowding games. He studies crowding games with "non-anonymous" players where the payoff function varies among agents. Then he shows that crowding games with non-anonymous players do not possess an equilibrium in general. Bogomolnaia and Nicolo (2005) study the stable assignment of public facilities in the presence of consumption externality. Then they show that there is no strategy-proof, efficient, and stable

[1] The conditions for optimal allocation have been analyzed in the previous theoretical literature. See for example, Oakland (1972) and Berglas and Pines (1981).

[2] Anonymity presumes perfectly identical agents.

allocation rule if more than two groups have to be formed.

The assignment of public facilities is certainly an important research agenda. However, the relocation of public facilities requires substantial transaction costs and is not feasible in practice. Therefore, the government has to find the mechanism that resolves a congestion problem given the current location of public facilities.

Traffic congestion generates a huge economic loss. Congestion management (allocation of commuters to routes) has been an important problem in many countries. Selten et al. (2007) analyzes commuters route choice behavior in the laboratory. They find that subjects keep changing their routes even in the substantially long experiment. Then they conclude that fluctuation around the pure equilibrium is a much better explanation about commuters route choice behavior. This implies that the optimal allocation of the commuters can be achieved through voluntary sorting but the optimal allocation will not be maintained. The authors further examine whether additional feedback information (the provision of congestion information in the previous period) mitigates the congestion problems. They show that commuters change their routes less frequently when additional feedback information is provided.

The main object of this paper is to extend the analysis of Selten et al. (2007) by allowing cost heterogeneity across agents. If a chosen facility is crowded, an agent must wait in line until obtaining the service. Agents are heterogeneous and waiting costs should vary across agents. Some do not mind spending a reasonable amount of time in line but others are less patient. Both high and low-cost agents are using the same public facility in a real world. Therefore, it is worthwhile to examine how cost heterogeneity affects the facility choice of the agent.[3]

In this paper, we consider the following questions. Does cost heterogeneity affects the distribution of facility users? Does the high-cost agent change the facilities more or less frequently? Does the provision of additional feedback information reduce the frequency of facility changes even in the presence of cost heterogeneity? To answer these questions, we create an original computer network system and conducted laboratory experiments.

The economic agents may reach an equilibrium by some sort of an adaptation process (Kandori et al. 1993 and Young 1993). It would be worthwhile to identify the adaptation process that characterizes the facility choice behavior of the agents. Selten et al. (2007) employ a reinforcement learning model to simulate commuters' root choice behaviors. They identify the optimal parameter set of the reinforcement learning model that simulates the root selection of the commuters. In this paper, we create state-action tables based on the experimental data and simulate the facility selection of the agents. This is the approach commonly used in operation research literature.

[3] We will study non-anonymous crowding game in the present paper while Selten et al. (2007) study anonymous crowding game.

The structure of the remaining paper is as follows. The experimental set-up is explained in Section 2. The theory predicts that cost heterogeneity will not affect the facility selection of the agent. We will summarize the behavior of the agents in Section 3. The results show that cost heterogeneity does affect neither the facility selection of the agent nor the congestion level of facilities. In Section 4, we create state action tables to analyze the adaptation process of the agent. We consider two types of agents in simulations. The first type of agent is the one who chooses the next action according to the current congestion level. The second type of agent is the one who chooses the next action according to the reward change. We find that the simulation applying the former type of agents fits the laborary data better. We conclude the paper in Section 5.

2. Experimental set-up

Subjects are 40 students from the Department of Informatics of Kansai University, Japan. They were divided into 5 groups, with 8 subjects in each group. We conducted the same experiment for each group. The experiment had 5 sessions. In each session, subjects had to choose one of the two facilities (either facility A or facility B) 30 times repeatedly.

It is assumed that both facilities provide an identical service. However, the cost of using facility changes with the congestion level of a chosen facility. If subject i chooses facility n^A and the number of the subjects who choose facility A is n^A, then the period payoff (the unit is Japanese yen) becomes $v_i^A = 70 - c_i n^A$. Here, c_i is the subject-specific cost of using the facility. If subject i chooses facility B, then the period payoff becomes $v_i^B = 70 - c_i n^B$, where $n^B = 8 - n^A$ is the number of the subjects who choose facility B. Therefore, the expected cost and benefit of using the two facilities are the same.

In addition to the payoffs, every participant received a show-up fee of 2,000 yen. Before beginning the experiment, the leaflet that explained the purpose and the procedure of the experiment was given to the subjects. The leaflet is in Appendix A.

The first session is designed as the baseline case. We set $c = 6$ for all 8 subjects. In the remaining four sessions, we equally split 8 subjects into two subgroups: subgroup A and subgroup B. In Session 2, we set $c = 8$ for the subjects in subgroup A while we set $c = 4$ for the subjects in subgroup B. In Session 3, we swapped the costs between two subgroups and conducted the same experiment as in Session 2.

The main purpose of this experiment is to examine whether the cost difference in using facilities affects the facility choice behavior of the agents. We model the experiment as a repeated game. In our framework, only the congestion level influences the expected payoff. Therefore, all players equally evaluate the two facilities regardless of the cost. Consequently, a unique pure equilibria of all games is $n^A = n^B = 4$.

In the mixed equilibrium, every player chooses the both facilities with probability $x = \frac{1}{2}$. The computation of symmetric mixed equilibrium is reported in Appendix B. The expected sum of the number of players in all 30 periods is 120 in all three sessions: $4 \times 3 = 120$. Thus we expect that cost heterogeneity will not affect the distribution of the subjects across two facilities.

We further expect that cost heterogeneity will not affect the frequency of facility changes. The expected total number of facility changes is 116 in all three sessions: $\left(8 \times \frac{1}{2}\right) \times 29 = 116$.

In the first three sessions, the subjects received the following information at the beginning of each period:

- the number of the current session,
- the number of the current period,
- last chosen facility,
- payoff the last period,
- cumulative payoff in the session.

Selten et al. (2007) examined whether commuters route choice behavior was influenced by the provision of additional feedback information. Following their work, we provided the subject with addition feedback information in the last two sessions. The amount of the payoff of the non-chosen-facility in the last period was informed to the subject.

In the beginning of each session, we asked the subjects to answer several sample questions to examine whether they understood the procedures of the experiments. Appendix C-1 and C-2 are the typical screenshots that subjects saw during the experiment.

3. Observed Behavior

3.1 Cost Heterogeneity and User Distribution

Figure 1 shows the number of participants in Group 3 who chose Facility A in the first three sessions. It shows that substantial fluctuations persist until the end of the session. Convergence to the theoretical equilibrium was not observed in all three sessions.

Among five groups, the median number of subjects who chose Facility A is 4 in all three sessions. The averages are 4.03 in Session 1, 4.05 in Session 2, and 3.76 in Session 3. The corresponding standard deviations are 1.43 in Session 1, 1.37 in Session 2, and 1.26 in Session 3. The symmetric mixed equilibrium predicts a standard deviation of 1.41. Therefore, the observed standard deviation is larger than the predicted one in Session 1. However, the observed standard deviations are smaller than the predicted ones in Sessions 2 and 3.

As shown in Appendix B, the standard error for the mean of 5 groups is 3.46. The observed average numbers of subjects who chose Facility A are 120.8 in Session 1, 121.4 in Session 2, and 112.8 in Session 3. Thus, the hypothesis that the symmetric mixed equilibrium is played is rejected only in Session 3.[4]

No systematic difference is observed across three sessions. Hence, cost heterogeneity does not affect the user distribution.

3.2 Cost Heterogeneity and Facility Change

Figure 2 shows the number of participants who changed the facilities in the first three sessions. In the symmetric mixed equilibrium, the expected number of facility changes in each session is 116. The actually observed numbers are 80.2 in Session 1, 87.2 in Session 2, and 83.2 in Session 3. The results are reported in Table 1. The difference between the theoretical expectation and the observed value is greater than 8σ in all three sessions. Therefore, like Selten et al., the frequency of facility changes is much lower than the prediction by the symmetric mixed equilibrium.

To evaluate the impact of cost heterogeneity, we compare the fluctuations between Session 1 and Sessions 2/3. The null-hypothesis of no difference cannot be rejected by a Wilcoxon rank-sum test[5]. It implies that cost heterogeneity does not affect the fluctuation of facility congestion.[6]

3.3. Cost Heterogeneity and Agent Behavior

In Sessions 2 and 3, there are two types of players: high and low-cost players. Four subjects in Subgroup A are the high-cost player in Session 2 while remaining four subjects in Subgroup B become the high-cost player in Session 3. We compare the facility choice behavior between two types of players.

The number of high-cost players who changed the facilities in each period is 1.44 while the

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4 The hypothesis is rejected with much lower probability in Selten et al.'s study. Perhaps, the difference comes from the difference in experimental conditions. There are 18 subjects in Selten et al.'s study while there are only 8 subjects in our study. Also, subjects choose a route 200 times in Selten et al.'s (2007) study while subjects choose a facility 30 times in our study. We believe the experimental conditions are reasonable for the facility choice problem. Unlike a root selection, agents will not change their facility on daily base. It is less likely to find that more than 10 persons are in line.

5 The z value is -1.277.

6 We compared the fluctuations between Session 1 and Sessions 4/5. The null-hypothesis of no difference cannot be rejected again.

number of low-cost players is 1.47. Therefore, on average, low-cost players change the facilities more frequently. We compare the numbers of players who changed the facilities in each session. The null-hypothesis of no difference in switching behavior between two types of players cannot be rejected based on a Wilcoxon matched-pairs signed-rank test.[7] It implies that the cost difference does not influence the agent's facility choice behavior.

3.4. Effect of Congestion Information

Following Selten et al., we examine whether the provision of additional feedback information reduces the fluctuation. We compare the facility choice behavior of the agents between Sessions 2/3 and Sessions 4/5. The null-hypothesis of no difference across four sessions cannot be rejected by a Wilcoxon rank-sum test.[8] Unlike in Selten et al.'s experiment, we find that additional feedback information does not reduce the fluctuation of facility congestion.

4. Simulation-Based Test

4.1. Simulation Procedure

The purpose of this section is to simulate the facility selection of the agents. We consider three models. The first model is the random selection model in which all agents switch two facilities with deterministic probability schedule. In other words, an agent ignores the current distribution of the facility users on the next facility selection. The switching probability applied to the random selection model is 0.359, which is much lower than the switching probability of mixed equibrium.

The second model follows the reinforcement approach. It assumes that an agent decides whether he or she remains in the same facility or moves to the other facility in the next period according to the current congestion level. We call this second model "congestion response model." Using experimental data, we created the state-action table.[9] In the state-action table of the congestion response model, states are defined by the number of agents in the chosen facility. Taking account of the current congestion level, the agent chooses one of the two actions: "Stay" or "Move." The switching probability in Table 2 indicates the ratio of "Move" given the current congestion level. For example, the table shows that an agent moves to the other facility with probability 0.319 when two other agents are in the same facility as he or she chooses.

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[7] The z value is -0.674.
[8] The z value is -0.606.
[9] The table is created based on 5,800 observations = 8 persons × 29 periods × 5 sessions × 5 groups.

The third model follows the reinforcement approach also. However, it assumes that an agent decides his or her action based on the change in the reward condition. There are three states in this model: the reward decreased, remained the same, and increased from the last period. We call this third model "reward response model." The switching probability in Table 3 indicates the ratio of "Move" given the reward change. For example, the table shows that an agent moves to the other facility with the probability 0.415 if the reward decreased from the last period.[10] It is assumed that 8 agents choose one of the two facilities based on the above three decision rules. In each simulation, 8 hypothetical agents choose the facility 150 times. To find the general characteristics, we conducted 100,000 simulations.

In order to compare simulation and experimental results, we introduce the following measure.

$$AverageDifference = \frac{1}{P}\sum_{p=1}^{P}\frac{1}{M}\sum_{m=1}^{M}| capacity_m - user_{m,p} |$$

where P is the number of periods, M is the number of facilities, $capacity_m$ is the capacity of Facility m, and $user_{m,p}$ is the number of users who use Facility m at period p. In our experiment $P = 150$, $M = 2$ and $capacity_m = 4$. As the users are distributed efficiently, the average difference decreases.

4.2. Adaptation Process

Table 4 compares the average differences among three simulation models. The average difference observed in the laboratory experiment is 1.023. In contrast, the average difference simulated by the random selection model is 1.094. Thus, the facilities are used more efficiently than the prediction of the random selection model.

The congestion response model fits better than the reward response model. The results imply that the agent decides his or her action according to the current congestion level.

4.3. Cost and Individual Heterogeneity

We estimated the switching probabilities of low, middle, and high-cost agents. Applying these probabilities, we conducted the simulations. The results are presented in the second column of Table 4. The table shows that the inclusion of cost heterogeneity does not improve the simulation results. Like in Section 3, we find that the difference in the facility choice among agents cannot be explained by the cost difference.

[10] The table is created based on 5,600 observations = 8 persons × 28 periods × 5 sessions × 5 groups.

Finally, we created the state-action tables of each subject and conducted the simulation based on the 40-subjects tables. The results are presented in the last column of Table 4. The table shows that the inclusion of individual heterogeneity improves the simulation results at the great extent. However, it overly improves the efficiency of the facility use in the congestion response model.

In the simulation, an agent never changes his or her switching probabilities. However, during laboratory experiment, a subject changes his or her switching probabilities. Such a capricious response of the agent worsens the congestion problem.

5. Conclusion

In this paper, we conducted the laboratory experiment of congestion games. We extended the analysis of Selten et al. (2007) by allowing cost heterogeneity across agents. The payoff that the agent receives is determined solely by the total number of the agents choosing the same facility. However, the cost of congestion varies across agents.

In this non-anonymous congestion game, the theory predicts that cost heterogeneity will not influence agents' behavior. This paper provides the experimental evidence for the theoretical prediction. Thus, any systematic difference is not observed in the behavior between high and low-cost agents. They choose the facilities in the same manner.

We did not observe the convergence to the pure equilibrium. We observe fluctuation around the pure equilibrium. Although the optimal allocation of the users is achieved through voluntary sorting, it is less likely to be maintained.

When the deviation from the optimal allocation is unavoidable, we need to find the model that explains the switching behavior of the agent. Based on the simulation results, we find that the agents decide their action according to the congestion level of the facility.

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Figure 1. Number of players who chose Facility A (Group 3)

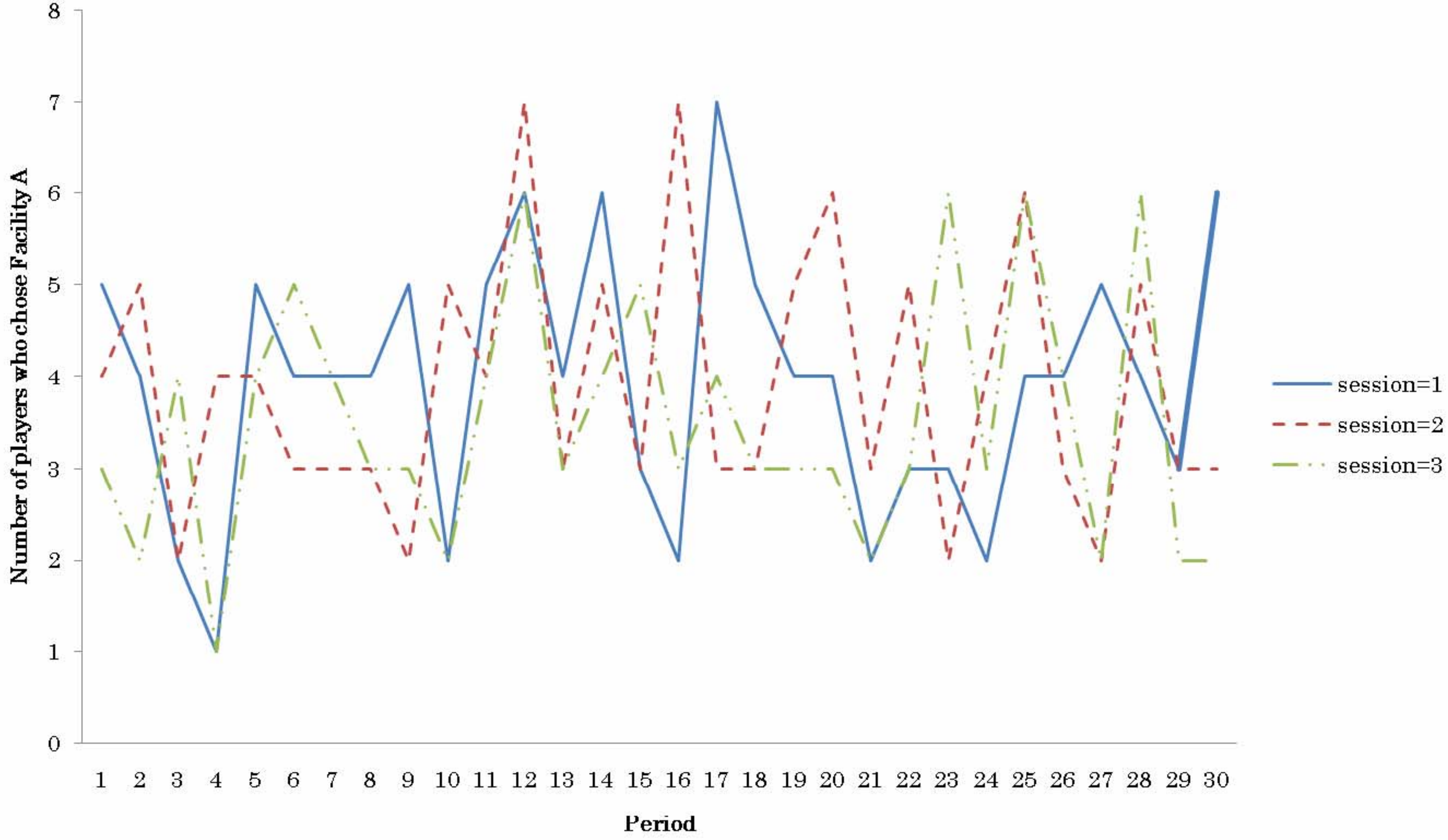


Figure 2. Number of players who changed facility (Group 3)

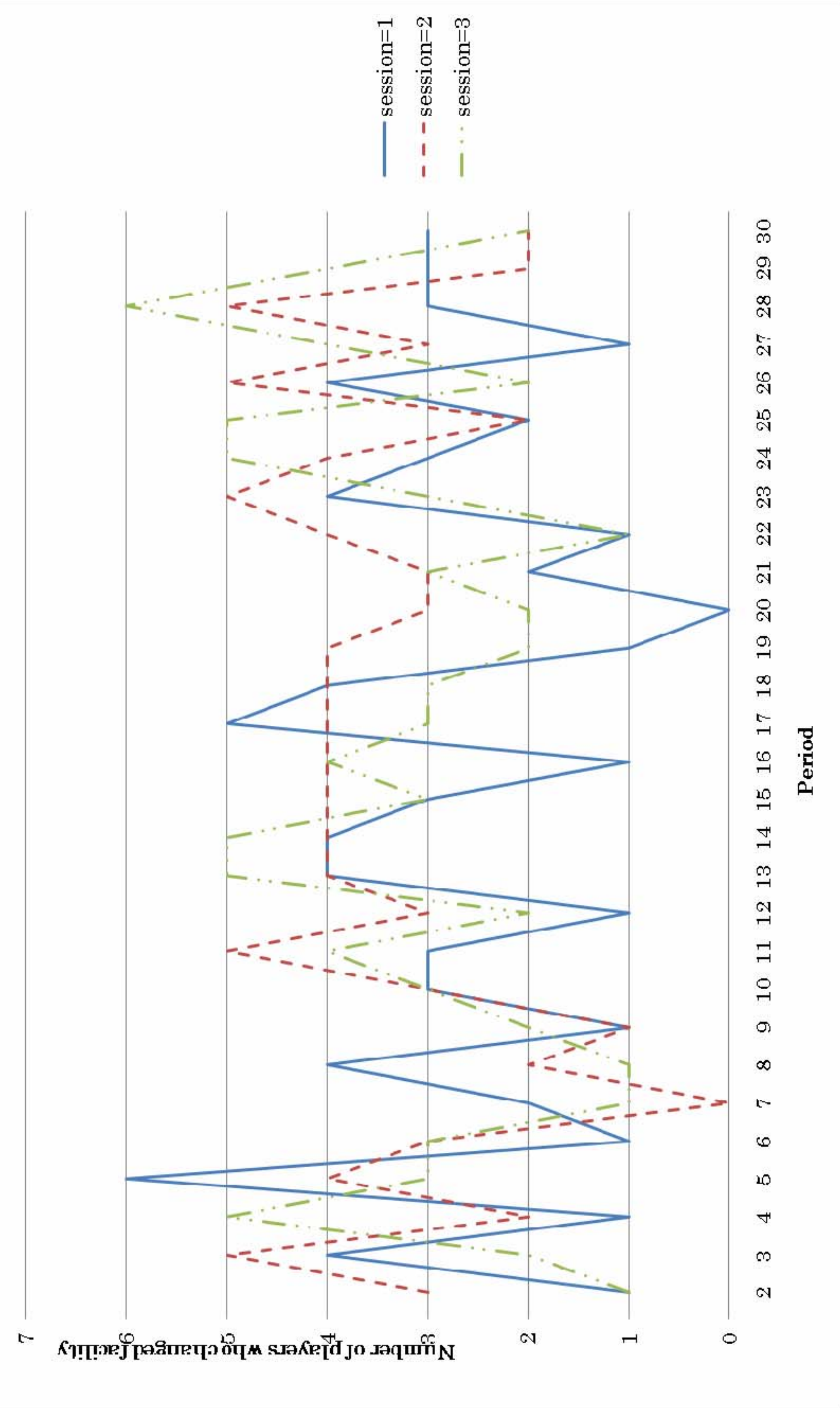


Table 1. Number of players who changed the facility

Group	Session	1	2			3			4			5		
		Total	High	Low	Total	High	Low	Total	High	Low	Total	High	Low	Total
1	Sum	69	43	27	70	27	26	53	44	25	69	39	27	66
	Mean	2.38	1.48	0.93	2.41	0.93	0.90	1.83	1.52	0.86	2.38	1.34	0.93	2.28
	STD *	1.01	0.99	0.70	1.05	0.70	0.67	0.89	1.06	0.74	1.40	0.94	0.75	1.00
	Median	3	1	1	2	1	1	2	2	1	2	1	1	2
2	Sum	88	26	37	63	51	57	108	46	49	95	51	49	100
	Mean	3.03	0.90	1.28	2.17	1.76	1.97	3.72	1.59	1.69	3.28	1.76	1.69	3.45
	STD *	1.68	0.72	0.84	1.14	1.15	0.78	1.67	0.98	1.11	1.31	0.95	1.04	1.18
	Median	3	1	1	2	2	2	3	2	2	3	2	2	4
3	Sum	75	45	50	95	39	52	91	53	45	98	34	42	76
	Mean	2.59	1.55	1.72	3.28	1.34	1.79	3.14	1.83	1.55	3.38	1.17	1.45	2.62
	STD *	1.50	0.99	1.10	1.75	0.90	0.86	1.09	0.76	0.83	1.27	0.97	0.99	1.54
	Median	3	1	2	3	1	2	3	2	1	3	1	1	3
4	Sum	85	59	44	103	45	45	90	45	35	80	34	44	78
	Mean	2.93	2.03	1.52	3.55	1.55	1.55	3.10	1.55	1.21	2.76	1.17	1.52	2.69
	STD *	1.07	0.94	0.63	1.15	0.95	1.02	1.21	0.83	0.86	1.21	0.80	0.83	1.04
	Median	3	2	1	4	1	2	3	1	1	3	1	1	3
5	Sum	84	39	45	84	45	44	89	31	27	58	55	52	107
	Mean	2.90	1.34	1.55	2.90	1.55	1.52	3.07	1.07	0.93	2.00	1.90	1.79	3.69
	STD *	1.21	1.14	1.15	2.02	1.09	0.95	1.60	0.88	0.92	1.13	1.05	0.94	1.39
	Median	3	1	2	2	1	2	3	1	1	2	2	2	4

* Standard Deviations

Table 2. State-Action Table (Congestion Response Model)

State Congestion Level	Switching Probability			
	Aggregate	Low-Cost (c=4)	Middle-Cost (c=6)	High-Cost (c=8)
1	0.410	0.400	0.333	0.471
2	0.232	0.207	0.224	0.265
3	0.319	0.303	0.324	0.332
4	0.313	0.285	0.372	0.315
5	0.387	0.407	0.321	0.400
6	0.439	0.498	0.356	0.426
7	0.487	0.469	0.476	0.516
8	0.438	0.375	0.550	0.500
Average	0.359	0.357	0.346	0.367

Table 3. State-Action Table (Reward Response Model)

State Reward Condition	Switching Probability			
	Aggregate	Low-Cost (c=4)	Middle-Cost (c=6)	High-Cost (c=8)
Decreased	0.415	0.365	0.342	0.379
Remained the same	0.351	0.336	0.327	0.355
Increased	0.312	0.361	0.358	0.363
Average	0.361	0.357	0.346	0.367

Table 4. Comparison among Simulations Evaluated by Average Difference

Model	Aggregate	Cost Heterogeneity	Individual Heterogeneity
Experimental Results	1.023	1.023	1.023
Random Selection Model	1.094	1.094*1	1.094*1
Congestion Response Model	1.037	1.043	1.013
Reward Response Model	1.061	1.054	1.047

Note.

*1. All agents are treated in the same manner. Thus, the numbers are the same as in aggregate.

Appendix A. Instruction to Subjects

2009/2

About Today's Experiment

We thank you for your participation to the PG Lab experiment. The purpose of this experiment is to examine how an individual changes his or her behavior using provided information. There are a few things to note about this experiment. Please read this instruction first.

Examples

Imagine the situation in which you are waiting for your turn in the line to obtain a service at a particular facility. For example, you are waiting your turn in front of ATM to withdraw your money or you are waiting your turn at the postal office to send your parcel. In these situations, you will obtain the same service regardless of the facility. Therefore, you will choose the least crowded facility.

Instruction of this experiment

- ✧ In this experiment, we will ask you to choose one of the two facilities repeatedly.
- ✧ If you choose the facility that a small number of people choose, then the waiting time becomes shorter. Consequently, your payoff becomes larger.
- ✧ Your cumulative payoff constantly changes with your facility selection.
- ✧ The cumulative payoff you obtained is shown on the PC screen in each period.
- ✧ The maximum payoff you can obtain through this experiment is 9,600 yen while the minimum one is 3,300.
- ✧ After each session, please fill your payoff in the prescribed form.
- ✧ In addition to the payoff you will obtain through the experiment, you will receive 2,000 yen remuneration.

Cautions

1. All instructions are provided on the PC screen. When you cannot understand them, please raise your hand and ask your questions to the instructor directly.
2. Please do not talk to other persons during this experiment
3. Please do not look at the other persons screen during this experiment.
4. Once this experiment begins, you cannot go to the bathroom for about one hour. Please go to the bathroom now if you want to.

Thank you for your cooperation

Appendix B. The Computation of Mixed Equilibrium

In this experiment, there are two types of agents, high-cost and low-cost agents. It is assumed that an agents know his or her own type only. Suppose H-type agent expects that other agents choose facilities A and B with probabilities x_H and $1-x_H$, respectively. Suppose L-type agent expects that other agents choose facilities A and B with probabilities x_L and $1-x_L$, respectively. The conditionally expected payoff is

$$E[U_{HA}] = V_A - c_H \left(1 + x_H (n-1)\right)$$

if H-type agent chooses facility A. That is

$$E[U_{HB}] = V_B - c_H \left(1 + (1 - x_H)(n-1)\right)$$

if he or she chooses facility B. Here, n is the total number of agents, c_H is the waitng cost of H-type agent, V_A and V_B are facility specific benefits. In equilibrium, the conditional expected payoff must be equal. The solution becomes

$$x_H = \frac{V_A - V_B}{2c_H (n-1)} + \frac{1}{2}.$$

Similarly, the solution for L-type agent becomes

$$x_L = \frac{V_A - V_B}{2c_L (n-1)} + \frac{1}{2}.$$

Since it is assumed that the two facilities provide the same service, $V_A = V_B$. Therefore, both high-cost and low-cost agents expect other agents choose the facility with probability 0.5.
The variance of a binomial distribution with success probability 0.5 is $V_X = 0.25$. The standard deviation for 8 subjects in one period is

$$\sigma_X = \sqrt{0.25 \times 8} = \sqrt{2}.$$

In each session, the number of the agents that uses either facility is $120 (= 30 \times 8 \times 0.5)$. The corresponding variance is

$$V = 30 \times 8 \times \frac{1}{4} = 60 .$$

Assuming 5 sessions are independent each other, then agent's facility selection is approximated by normal distribution:

$$N(nx, nx(1-x)) = N(120, 60) .$$

The variance for the man of 5 sessions is

$$\frac{V}{5} = \frac{60}{5} = 12 .$$

The corresponding standard error is

$$\sigma = \sqrt{12} = 3.464 .$$

The expected probability of facility changes is

$$y = 2x(1-x) = 2 \times \frac{1}{2} \times \frac{1}{2} = \frac{1}{2} .$$

Therefore, the expected number of facility changes is

$$R = (30-1) \times 8 \times \frac{1}{2} = 116$$

The variance of it is given by

$$V_y = y(1-y) = \frac{1}{4} .$$

The variance of R is

$$V_R = (30-1) \times 8 \times V_y = 58 .$$

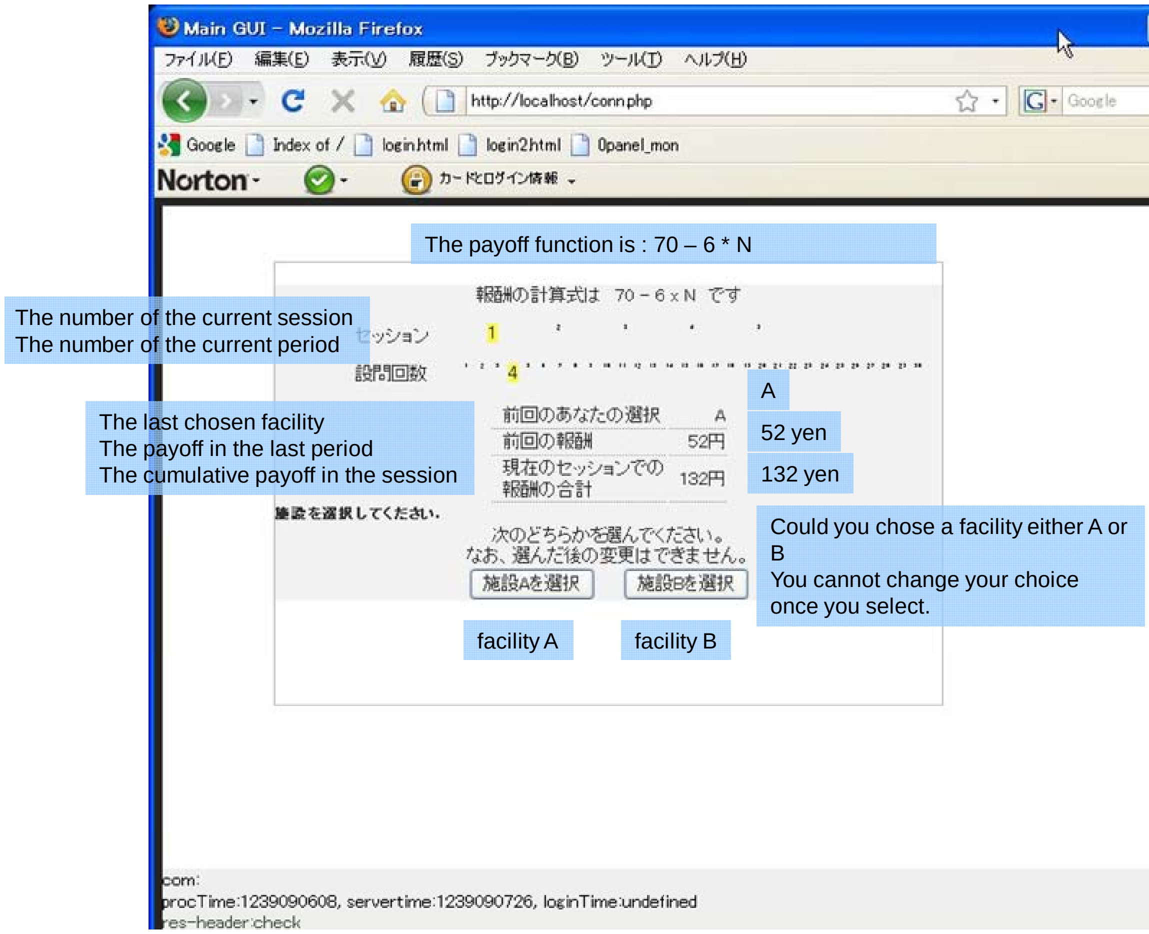
The variance for the man of 5 sessions is

$$\frac{V_R}{5} = \frac{58}{5} = 11.6 \,.$$

The corresponding standard error is

$$\sigma_R = \sqrt{11.6} = 3.406 \,.$$

Appendix C-1 Screen shot example of the first three sessions



Appendix C-2 Screen shot example of the last two sessions