RCSS ディスカッションペーパーシリーズ ISSN-1347-636X
第 93 号　2010 年 2 月
Discussion Paper Series
No.93 February, 2010

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Research Center of Socionetwork Strategies,
“Academic Frontier” Project for Private Universities, 2003-2009
Supported by Ministry of Education, Culture, Sports, Science and Technology
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A Micro Data Analysis on Individual's Deposit-Withdrawal Behavior*

Proposal of Micro Financial Policy Tool

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Abstract. Our purpose of this paper is to investigate relationships between individual's deposit-withdrawal behavior and factors behind them using micro data collected from a Web-based survey that we conducted in March 2009. As a result, we find some relationships between individual's deposit-withdrawal behavior, and economic and psychological factors. For example, we confirm that the probability that they withdraw their deposits tends to be lower if individuals correctly recognize Japanese deposit insurance scheme. In other words, this suggests having to make people understand the scheme. In addition, it is found that individual attributes like education and marriage status influence deposit-withdrawal behavior and by differences of the failure probability the effects are different, too.

Keywords: Depositor behaviors, psychological factor, communication, logistic regression analysis, Web-based survey
JEL Classification Codes: C25, C91, Z13

1 Introduction

Problems of subprime loan and failure of Lehman Brothers became one trigger to give a harsh blow to economies of not only the United States but also all of other countries. Then, many of companies decreased their revenues and some ones went bankruptcy. In the United States and the United Kingdom, financial panics like bank runs occurred. Japan is not an exception and faces the state of

* This work was supported by the Joint Usage/Research Center from MEXT, Japan and the JSPS Grant-in-Aid for Exploratory Research (19653027). We are thankful to Professor, Ukai, Y. (Kansai University, Japan), Assistant Professor, Murakami, M. (Kansai University), Assistant Professor, Ichikawa, K. (Osaka University, Japan), Assistant Professor, Kobayashi, T. (National Institute of Informatics, Japan) for variable comments.

Depression. Therefore, Japanese government implements various economic and monetary policies, but we cannot necessarily accept that these policies worked effectively. By using analysis results based on the macroeconomic model, many economists discuss the effect of economic and monetary policy to recover from the state of Depression, for example, Choe and Lee (2003), and Pathan, Skully and Wickramanayake (2008). An approach based on macroeconomic model is effective to analyze influence of the whole economy, but many of analysis results might have little flexibility inevitably. In the model individual behavior assumed is just average or representative and data for analyzing it is aggregated. Especially, it might be doubtful that macroeconomic model can correctly capture people's behavior in a panicky situation. This seems to be one limit of approach based on macroeconomic model to the economy where finance is unstable or is in the state of Depression. As one of the approaches that overcome this limit, we have an approach based on microeconomic model where we can analyze economic effects of individuals and/or companies and approach based on microeconomic model is remarkable recently. A reason is that a microeconomic model can adopt factors which cannot build in macroeconomic model and the analysis results have sufficient possibility of giving richer suggestions rather than ones based on macroeconomic model.

In this paper, given the economy where finance is unstable or is in the state of Depression, we quantitatively approach to individual's deposit-withdrawal behavior by a microeconomic model. In other words, we capture individual behavior in a panicky situation by using microeconomic model and analyze it. Consequently, we can obtain a clue that we understand a situation of financial panic like a bank run, which many individuals withdraw their deposits almost at the same time. This is able to give some materials to avoid bank run and/or settle it even if it occurred. That is, this paper shows information on a bank run mechanism and we can offer it to financial institution and government[1].

There are a lot of qualitative studies on bank runs and finance crisis, for example, Shiller (2008). On the other hand, studies based on data analysis are new and challenging, and the accumulation of such studies is considerably few: Takemura and Ukai (2008), Takemura and Kozu (2009), Yada et al (2008) and Yada, et al (2008, 2009)[2].

Takemura and Ukai (2008) and Takemura and Kozu (2009) statistically analyze individual's deposit-withdrawal behavior in Japan using micro data collected from a Web-based survey by themselves, and clarify some factors that influence their behaviors. They suggest that banks and authorities have to pay attention to information sources which individuals frequently use and if the chain of uneasiness could be blocked with such knowledge, it might be possible to avoid unnecessarily panics. Besides, they confirm that there are no statistical relation-

[1] These studies are also important when we analyze the financial crises from the viewpoints of economics, but they do not necessarily lead to a social simulation in this paper we propose.

[2] It seems that this reason is that micro data on deposit-withdrawal behavior is not accumulated almost.

ships between individual's deposit-withdrawal behavior and economic variables such as annual income, amount of deposit and the number of accounting. Yada et al (2008, 2009) analyze individual's deposit-withdrawal behavior using the same micro data and data-mining technique, and clarify some factors that influence their behaviors[3]. In addition, they estimate total amount of deposit in each branch of financial institution should prepare if a bank run occurred.

In this paper, we attempt to refine the model in Takemura and Kozu (2009) using micro data collected from a Web-based survey that we conducted in March 2009, and investigate relationships between individual's deposit-withdrawal behavior and factors behind them. By doing so, we suggest possible countermeasures whereby depositors will not excessively withdraw their deposits after receiving uncertain information on the financial environment.

This paper is organized as follows. In section 2, we present our model and explain the statistical method and data set. Section 3 shows the estimated results and the implications. In section 4, we propose a micro financial policy tool. Finally, we conclude remarks and show future work in section 5.

2 Framework

2.1 Model and Statistical Method

Takemura and Kozu (2009) model individual's deposit-withdrawal behavior after receiving insecurity information on financial environment and analyze it using framework of a logistic regression model[4]. In this paper, we attempt to refine the model.

Similarly, we build a model by binary logistic regression equation, which explained variable is the probability that individuals withdraw their deposits after receiving insecurity information on financial environment and explanatory variables are grouped roughly as follows: 1) degree of trust in information sources, X_1, 2) the number of friends or colleagues exchanging information, X_2, 3) individual transactions with banks, X_3, and 4) individuals' attributes, X_4. Instead of frequency of communication used in Takemura and Kozu (2009), we afresh use the number of friends or colleagues exchanging information. By using this factor, we can discuss information diffusion on individual's deposit-withdrawal behavior. This is one of new challenges different from the model in Takemura and Kozu (2009). As the other challenges, we use more sophisticated micro data rather than ones in Takemura and Kozu (2009). Section 2.2 will explain these variables in detail.

[3] Some individual attributes that influence the deposit drawing out action are different though they use and are analyzing the same data according to the difference of the approach. They use the same micro data used in Takemura and Kozu (2009), but according to a difference of approach, factors that influence deposit-withdrawal behaviors are somewhat different. Refer to both papers for details.

[4] Logistic regression model has been widely used for building a decision making model as a statistical method to grasp the relationships among explanatory variables and explained variables in many fields like psychology, sociology and economics.

After receiving information on failure probability of individual's main bank, k (%), the relationship between the explained variable and the explanatory variables is simply described by equation (1).

$$\log \frac{p_k}{1-p_k} = b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 \tag{1}$$

where p_k is the probability that individual withdraws his deposit after receiving information on failure probability of his main bank, k (%), and b_j $(j = 1, 2, 3, 4)$ represents a logarithm odds of variable X_j. This can be interpreted as the degree to which individuals are apt to withdraw their deposits. For example, if X_j with the ordinary property changes one unit and the coefficient parameter bj is positive (resp. negative), then individuals are apt to (resp. not to) withdraw all of their deposits after receiving information on failure probability of his main bank. On the other hand, if coefficient parameter of a variable is zero, the factor does not influence individual's deposit-withdrawal behavior. A bank run will occur if enough number of individuals withdraw their deposits, and such a situation is a risky one for banks. Therefore, it is important to know the signs of variables in equation (1) when we understand a situation of bank run mechanism.

Our model expressed by equation (1) is incorporating not only economic variables, but also psychological ones in the decision-making of depositors. We assume that depositors would be strongly affected by psychological factors if they encounter a financial panic situation such as a bank run. A microeconomic model is able to adapt some psychological factors to a model. As psychological factors, we use degree of risk aversion, rate of time-preference and degree of trust in information sources.

Briefly, here, we explain methods and processes to estimate coefficient parameters in equation (1) and to evaluate the fit of our model. Generally, to estimate each coefficient parameter in equation (1), we use the general maximum likelihood estimation method based on a binominal distribution, and a computer software for statistical analysis is used as the calculation of the estimations is too complex. In this paper, first all variables concerning with deposit-withdrawal behavior collected from the survey are incorporated into equation (1), and next we adopt the method of searching for combination of variables that maximize the likelihood in equation (1) while deleting variables, called the variable decrease method. That is, the results are combination of statistically significant variables which maximize the likelihood[5].

Next, we evaluate the fitness and the validity of the model by running the Hosmer-Lemeshow test and using a positive distinction rate, which measures the fit of this model. Refer to Hosmer and Lemeshow (2000) about the details of this test.

[5] During the process, if there variables do not influence or have statistically no relations with deposit-withdrawal behavior, they would be eliminated from equation (1) by turns.

2.2 Data set

By changing environment of social survey such as mail survey, interview survey and telephone survey at recent years, the difficulty of survey increases gradually[6]. That is, it is hard to be receiving the cooperation of respondent in individual survey. Therefore, in spite of many researchers' efforts, most of them can fail to achieve anywhere near an acceptable response rate in many surveys. On the other hand, Web-based survey is paid attention as a new approach in the field of marketing research[7]. It is not necessarily a mistake to adopt Web-based survey as one approach if aim of the survey is to offer judgment materials that is useful for individual and organization's decision making; the Japan Institute for Labour Policy and Training (2005). Of course, we must discuss the accuracy of the survey. Unfortunately, we cannot compare because there is no similar survey that others conduct. Then, we take cognizance of this data without generality necessarily, and use the data set in this paper. In the future, we will need to discuss utilization of data collected from a Web-based survey[8].

In this paper, we use data collected from Web-based survey that we conducted at March 2009[9]. Subject of this survey are Japanese who have more than one bank account and more than four friends frequently taking communications. Here, we will briefly explain the reason to target individuals who have more than four friends. To build a network where the interactions between individuals are represented, we need to know statistical distributions on degree, clustering coefficient and betweenness of the network[10]. Because it is generally expected that degree of the network is more than four, we impose this condition. In addition, samples of this survey are arranged by three axes; gender, age and living area in Japan[11].

The aim of this survey is to capture individual's deposit-withdrawal behavior from the viewpoints of economics, psychology and social network. This survey asks more than 50 question items such as gender, annual income, degree of

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6 According to the Japan Institute for Labour Policy and Training (2005), as various environmental changes, for example, there are decrease in recovery rate, an increase at refusal rate, rise of excessive privacy consideration and tightening regulation such as protection of individual information. In addition, nowadays, a list of names utilized in sampling is easily unavailable because using the list is limited.

7 Couper (2000) review issues and approaches on Web-based surveys.

8 For example, Ohsumi (2002) gives some suggestions on the limit and the possibilities of Web-based surveys in the future.

9 You can gain these survey slips by accessing to RISS's Website: http://www.kansai-u.ac.jp/riss/en/shareduse/database.html.

10 In Ichikawa et al (2009, 2010), they challenge to rebuild a social network based on the data collected from Web-based surveys and a generic algorithm (GA) and discuss employing the rebuilt network to social simulation.

11 For arranging three axes, we use the data on the number of population by age group and prefecture divisions in "the number of population and household movements based on basic resident register at 31st, March, 2008" (the Ministry of Internal Affairs and Communications; MIC). URL: http://www.soumu.go.jp/menu_news/s-news/2008/080731_6.html.

trust in information sources, degree of risk aversion, and the number of friends. This survey has 1365 respondents and the sample size excludes persons have completely contradicted answer or missing values.

Individuals' deposit withdrawal behavior The event for the explained variable in equation (1) is whether an individual will withdraw his entire deposit or not after receiving information on failure probability of his main bank, $k\%$ (k is in interval [0,100]). Other actions such as withdrawal of a part of his deposit are not considered in this paper. Thus, the explained variable in equation (1) is defined as follows:

$$p_k = \begin{cases} 1 & \text{if he withdraws his deposit,} \\ 0 & \text{otherwise,} \end{cases}$$

where p_k represents the probability that individual withdraws his deposit after receiving information on failure probability of his main bank, k (%).

In this survey, we ask questions on deposit-withdrawal behavior given nine kinds of different failure probability of his main bank; $k = 0.1, 0.5, 1, 2, 5, 20, 30, 50, 99$. Fig. 1 shows distributions for deposit-withdrawal behavior. When a failure probability of his main bank is 5%, most half number individuals intend to withdraw their deposits. It seems that a relation between failure probability and ratio of individuals withdrawing deposit draws the S-curve. Then, as a feature, ratio of individuals withdrawing deposit is about 14.0% even if a failure probability of his main bank is 0.1% and ratio of individuals not withdrawing deposit is about 7% even if a failure probability of his main bank is 99%. In the former case, many of them answer that they withdraw their deposits if there is a little failure probability ($k > 0$). On the other hand, in the latter case, many of them answer that they never withdraw their deposits because the deposits are guaranteed by Japanese deposit insurance scheme.

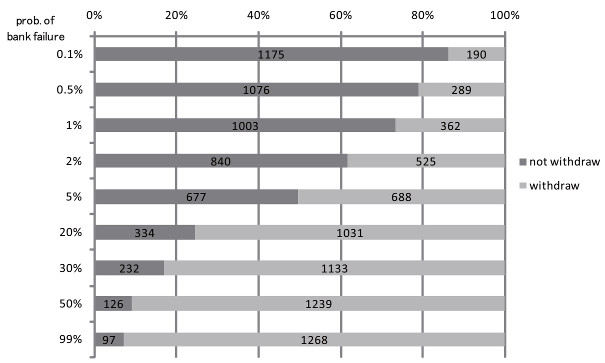

Fig. 1. Distribution for deposit-withdrawal behavior

Degree of trust in information sources In Takemura and Kozu (2009), they find that some degree of trust in information source influences individual's deposit-withdrawal behavior. In this survey, we ask questions on degree of trust in information sources separately for good news and bad news. And, as information source, we use (1) TV, X_{11}, (2) News paper, X_{12}, (3) Internet, X_{13}, (4) conversations with neighbors, X_{14}, (5) conversations with people at the workplace, X_{15}, (6) e-mail or phone call with friends, X_{16}, (7) weekly/monthly magazines, X_{17}, and (8) stranger conversations, X_{18}.

Distributions for degree of trust in information sources are shown in Fig. 2. We can check that degree of trust in information sources is different by each source. In addition, as the overall tendency, we find no great disparity of trust degree in between good news and bad news.

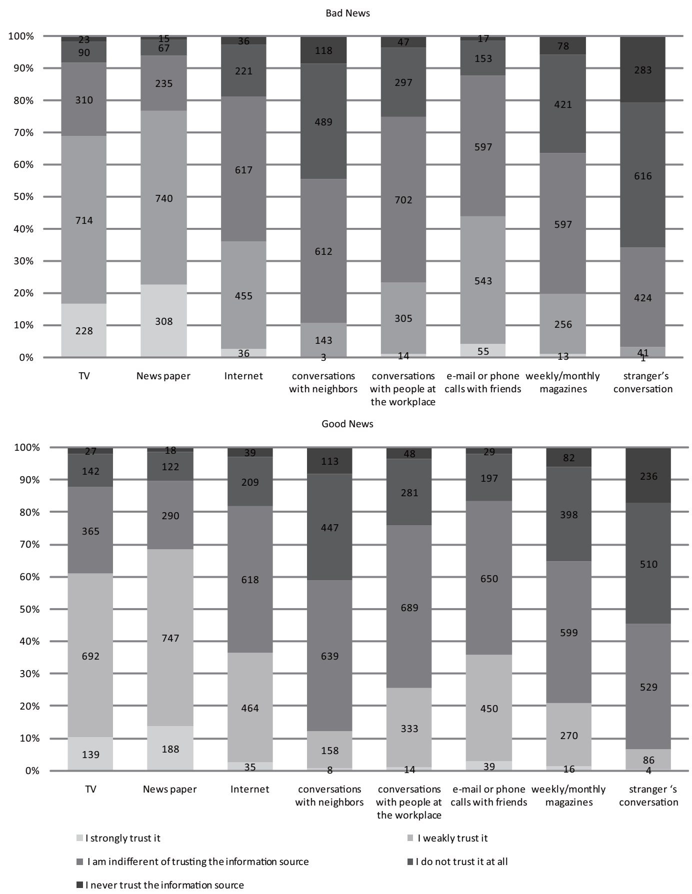

Fig. 2. Degree of trust in information sources

In this paper, because we consider insecurity information on failure probability of individual main bank, we use degree of trust in information sources in bad news.

The number of friends or colleagues exchanging information Through not only mass media such as TV, news paper and the Internet but also closed individual interactions, information spreads. Individual interactions play the important role in his decision-making as thought in game theory. When we analyze it using micro data, we need to obtain the data on the number of friends or colleagues frequently exchanging information. In this survey, we ask questions on the number of friends or colleagues exchanging information, X_{21}, and the number of friends or colleagues may influence his deposit-withdrawal behavior, X_{22}.

Distributions for the number of friends or colleagues frequently exchanging information are shown in Fig. 3. The average (median) number of friends or colleagues is 9.39 (resp. 7) persons.

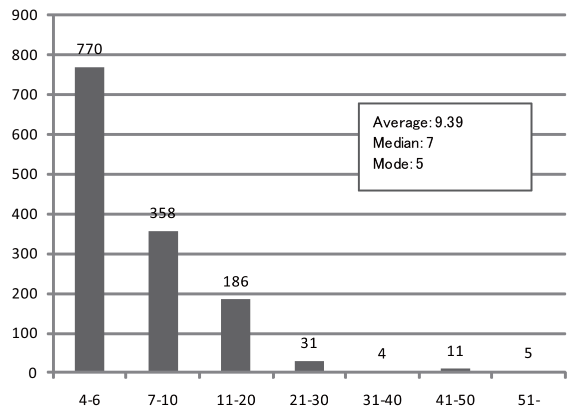

Fig. 3. Distribution for the number of friends or colleagues exchanging information

Fig. 4 shows distributions for ratio of friends or colleagues rumor failure of bank. We note that respondent's ratios exceed 100 (%) because some people answer exceed the number of friends or colleagues frequently exchanging information. We think the reason is that the number of friends or colleagues includes individual who does not exchange information so much. Thus, we uniformly convert the ratio into 100%.

The average (median) ratio of friends or colleagues rumor failure of bank is 43.18 (resp. 37.5)%.

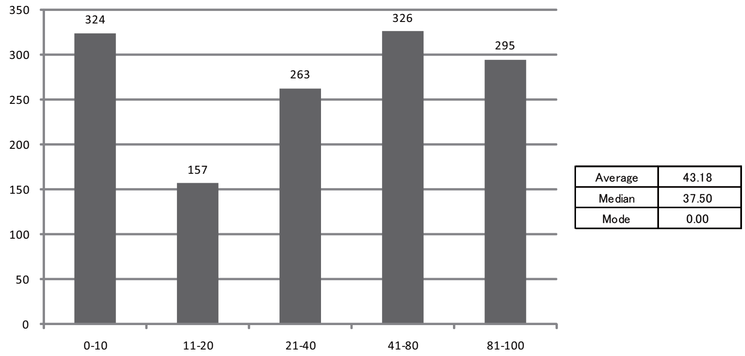

Fig. 4. Distribution for ratio of friends or colleagues rumor failure of bank

Transactions of individuals with banks To capture the transactions of individuals with banks, we use four variables; the number of bank accounts, X_{31}, total amount of deposit, X_{32}, type of main bank, X_{33} and recognition of Japanese deposit insurance scheme, X_{34}. In this survey, we ask questions on the number of bank accounts, amount of bank account with most deposits, type of main bank and recognition of Japanese deposit insurance scheme.

The number of bank accounts is a substitute variable that individual intend to decentralize his deposit and total amount of deposit is needed to judge whether or not his deposit are protected by Japanese deposit insurance scheme. Table 1 and Fig. 5 show elementary statistics on the number of bank accounts and distribution for total amount of deposit, respectively. Median and mode of total amount of deposit is 1-2 million yen and less than one million yen.

Table 1. Elementary statistics on the number of bank accounts

Average	Median	Mode	Standard deviation	Kurtosis	Skewness
4.116	4	3	2.302	30.447	3.844

Type of main banks is defined by using the following indicator function:

$$X_{33} = \begin{cases} 1 & \text{if individual uses mega bank including Yucho bank as main bank,} \\ 0 & \text{otherwise} \end{cases}$$

where mega banks are Tokyo Mistubishi UFJ bank, Mitsui Sumitomo bank, Mizuho bank and Resona bank. Fig. 6 shows distribution for individuals using main bank.

In Yada et al (2009), they find that recognition of the Japanese deposit insurance scheme influences individual's deposit-withdrawal behavior. They point

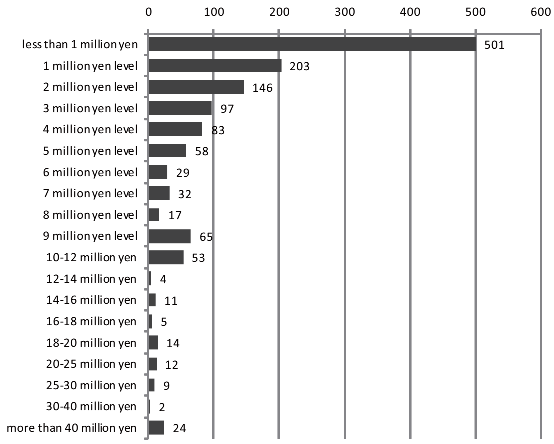

Fig. 5. Distribution for total amount of deposit

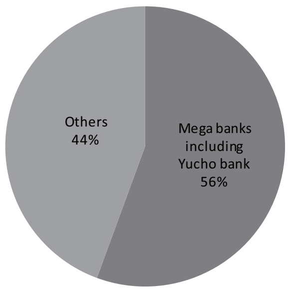

Fig. 6. Distribution for individuals using main bank

out that this variable is one of important factors. In Japanese deposit insurance scheme, deposit up to 10 million yen is guaranteed as an upper limit even if bank fails. From Fig. 5, we can find that the scheme is applied to 90.2% of respondents. Though their deposits guaranteed by the scheme, as you see in Fig. 1, all of them are going to withdraw their deposits after receiving insecurity information. This seems to imply that they do not know Japanese deposit insurance scheme. Therefore, we use the recognition of Japanese deposit insurance scheme, as one of variables. In this paper, the recognition of Japanese deposit insurance scheme is defined as follows:

$$X_{34} = \begin{cases} 1 & \text{if depositor recognizes Japanese deposit insurance scheme,} \\ 0 & \text{otherwise.} \end{cases}$$

Fig. 7 shows distribution for depositor recognizes Japanese deposit insurance scheme. In a question on recognition of Japanese insurance scheme, we ask to respondent whether or not to consider the scheme even if he knows, too. As the result, 52.8% of them answer that they know the scheme but do not consider it[12]. We note that in this paper, we do not regard these answers as recognizing the scheme and they are included in no recognition in Fig. 7.

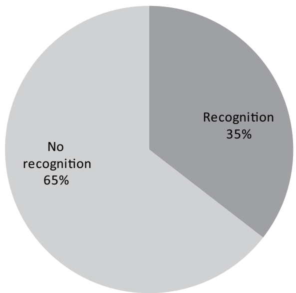

Fig. 7. Distribution for depositor recognizes Japanese deposit insurance scheme

Individuals' attributes As popular variables for individuals' attributes, we use gender, X_{41}, age, X_{42}, living area in Japan, X_{43}, education, X_{44}, marriage status, X_{45}, annual income, X_{46}, and amount of debt, X_{47}. By using the number of population by age group and prefecture divisions of the MIC in Japan, we arrange the data on gender, age and living area in Japan. See footnote 11). And, Fig. 8-11 show distributions for education, marriage status, annual income and amount of debt, respectively.

Annual income of 19% of respondents is less than five hundred thousand yen and the median value is 2-2.5million yen. Because this sample includes house wives (20.9%) and students (4.5%), the median value stays low. About debt, about 73% of respondents answer no debts[13].

As psychological factors used in economics, we have degree of risk aversion, X_{48}, and rate of time-preference, X_{49}.

In this paper, we apply the degree of absolute risk aversion used in Cramer et al (2002). The absolute risk aversion (RA) is calculated by the following

[12] In this survey, we do not show the scheme first. By doing so, as an experiment we can confirm the difference of whether to make decision after they know the scheme. Therefore, we show this question on the way. In the future, we will discuss this classification in other paper.

[13] There may be some respondents who answer as zero even if he has debt because this question is very naive content. Thus, the number of no debt may be overmuch.

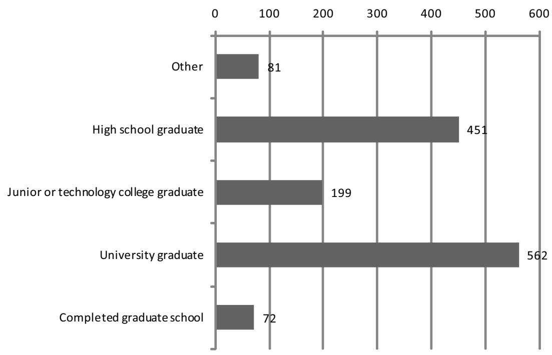

Fig. 8. Distribution for education

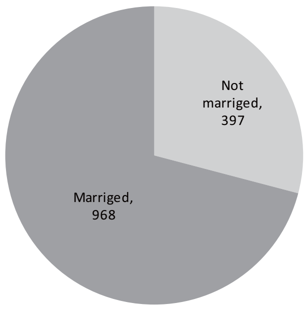

Fig. 9. Distribution for marriage status

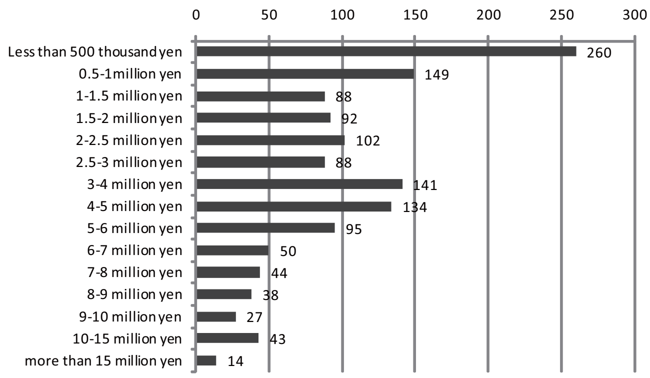

Fig. 10. Distribution for annual income

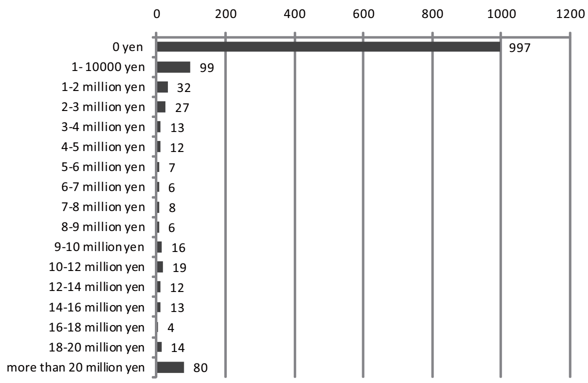

Fig. 11. Distribution for debt

equation:

$$X_{48} = \frac{aZ - r}{1/2[aZ^2 - 2aZ + r^2]} \tag{2}$$

where Z, a and r represent reward of lottery, winning probability, and price of lottery, respectively. X_{48} would be positive (negative) if you are risk aversion (loving), and X_{48} would be zero if you are risk neutral. To calculate X_{48} by using equation (2), given Z and r, we need to obtain a. In this survey, we ask how much respondent pay for lottery given $r = 1/100$ and $Z = 100000$ (yen). Fig. 12 shows distribution for X_{48} calculated by using equation (2). You can check that almost of them are risk-averse. The average and median is 0.001248 and 0.001399, respectively.

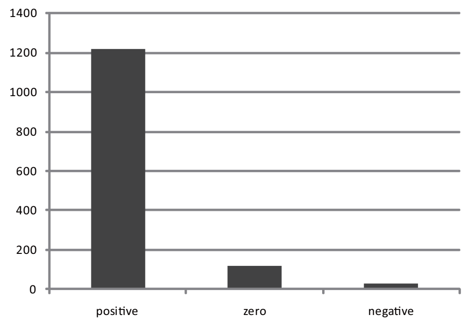

Fig. 12. Distribution for degree of risk aversion

About rate of time-preference, in this survey we ask that respondents compare lists of 10000 yen after 1 month and 13 months (with 8 kinds of interests) and which they select. Then, we calculate the rate of time-preference based on the information. Fig. 13 shows distribution for rate of time-preference. The average and median is 11 (%) and 8 (%), respectively.

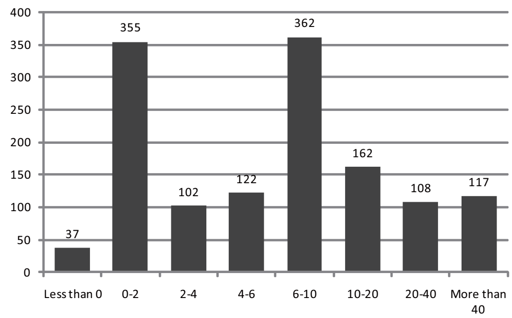

Fig. 13. Distribution for rate of time-preference

You refer to Ohtake and Tsutsui (2005) about concrete process of calculating degree of risk aversion and rate of time-preference.

3 Estimated Results and Implications

In this section, we estimate the coefficient parameters in equation (1) by running the variable decrease method by likelihood ratio. In this paper, we use PASW Statistics 18 as computer software for statistical analysis. We use nine kinds of different failure probability of main bank and 23 explanatory variables that we beforehand introduced in section 2.2. For readers' convenience, we show a list of all explanatory variables in Table 2.

Tables 3 and 4 show statistics for using tests and estimated parameters in equation (1), respectively.

From results in Table 3, we can evaluate the fit of these models. The both models are 5% or more significant. In addition, we can say the both models are valid also because the positive distinction rate turns out to be between56% and 93%.

From Table 4, by differences of the failure probability in section 2.2, it is found that variables finally survive in the process of the variable decrease method by likelihood ratio are different. Here, we briefly summarize dissimilarity between results.

Table 2. Explanatory variables' descriptions

Variable	Description
X_{11}	Degree of trust in TV
X_{12}	Degree of trust in News paper
X_{13}	Degree of trust in Internet
X_{14}	Degree of trust in conversations with neighbors
X_{15}	Degree of trust in conversations with people at the workplace
X_{16}	Degree of trust in e-mail or phone call with friends
X_{17}	Degree of trust in weekly/monthly magazines
X_{18}	Degree of trust in stranger conversations
X_{21}	The number of friends or colleagues frequently exchanging information
X_{22}	The number of friends or colleagues rumor failure of bank
X_{31}	The number of bank accounts
X_{32}	Total amount of deposit
X_{33}	Type of main bank
X_{34}	Recognition of Japanese deposit insurance scheme
X_{41}	Gender
X_{42}	Age
X_{43}	Living area in Japan
X_{44}	Education
X_{45}	Marriage status
X_{46}	Annual income
X_{47}	Amount of debt
X_{48}	Degree of risk aversion
X_{49}	Rate of time-preference

Table 3. Summary of Statistics

Case	-2 LL	Cox-Snell R^2	Nagelkerke R^2	Chi^2	p-value	p.d. rate	# of steps
1)	1071.223	0.452	0.603	9.941	0.269	86.2	14
2)	1379.245	0.313	0.418	6.962	0.541	78.8	17
3)	1562.587	0.215	0.286	5.020	0.755	73.5	17
4)	1789.336	0.073	0.097	9.352	0.314	61.5	17
5)	1848.106	0.032	0.042	8.066	0.427	56.3	16
6)	1446.807	0.278	0.371	8.865	0.354	75.7	14
7)	1151.348	0.419	0.559	7.171	0.518	83.2	14
8)	756.504	0.565	0.753	5.434	0.710	90.8	14
9)	643.123	0.600	0.799	13.395	0.099	92.8	15

LL: Log likelihood, p.d. rate: positive distinction rate

Table 4. Summary of Estimated Results

CASE		B	S.E.	Exp(B)
1	X_{12}	-0.202	0.099	0.817
	X_{13}	-0.141	0.107	0.869
	X_{14}	-0.142	0.106	0.867
	X_{17}	0.263	0.112	1.301
	X_{21}	0.006	0.004	1.006
	X_{22}	-0.038	0.018	0.963
	X_{34}	-0.337	0.173	0.714
	X_{42}	0.012	0.006	1.012
	X_{44}	-0.242	0.066	0.785
	X_{45}	-0.355	0.199	0.701
2	X_{12}	-0.102	0.078	0.903
	X_{13}	-0.195	0.090	0.823
	X_{14}	-0.165	0.089	0.848
	X_{17}	0.266	0.094	1.305
	X_{22}	-0.026	0.011	0.975
	X_{34}	-0.379	0.146	0.685
	X_{44}	-0.127	0.055	0.881
3	X_{11}	-0.128	0.076	0.880
	X_{13}	-0.156	0.079	0.855
	X_{17}	0.116	0.084	1.123
	X_{22}	-0.013	0.007	0.987
	X_{34}	-0.455	0.134	0.635
	X_{45}	-0.200	0.118	0.819
	X_{46}	0.037	0.016	1.037
4	X_{13}	-0.160	0.063	0.852
	X_{17}	0.101	0.069	1.106
	X_{22}	-0.002	0.002	0.998
	X_{44}	-0.123	0.047	0.884
	X_{32}	0.026	0.014	1.026
	X_{34}	-0.531	0.122	0.588
	X_{46}	0.039	0.016	1.040
5	X_{14}	-0.099	0.071	0.906
	X_{16}	0.130	0.066	1.139
	X_{22}	-0.008	0.005	0.992
	X_{34}	-0.515	0.117	0.598
	X_{42}	0.007	0.004	1.007
	X_{45}	-0.301	0.138	0.740
	X_{46}	0.050	0.015	1.051
	X_{47}	-0.019	0.013	0.981
6	X_{12}	0.190	0.068	1.209
	X_{16}	0.155	0.080	1.167
	X_{18}	-0.117	0.083	0.890
	X_{22}	-0.007	0.004	0.993
	X_{33}	0.274	0.129	1.316
	X_{34}	-0.806	0.133	0.447
	X_{42}	0.006	0.004	1.006
	X_{46}	0.044	0.018	1.044
	X_{47}	-0.029	0.014	0.972
	X_{48}	-8020.194	6215.550	0.000
7	X_{12}	0.210	0.082	1.234
	X_{14}	-0.232	0.102	0.793
	X_{16}	0.282	0.099	1.326
	X_{22}	-0.005	0.003	0.995
	X_{31}	0.066	0.038	1.069
	X_{33}	0.280	0.150	1.323
	X_{34}	-1.183	0.154	0.306
	X_{42}	0.009	0.004	1.009
	X_{44}	0.090	0.064	1.094
	X_{47}	-0.035	0.014	0.965
8	X_{11}	0.230	0.105	1.259
	X_{14}	-0.243	0.136	0.784
	X_{16}	0.280	0.129	1.323
	X_{22}	-0.002	0.001	0.998
	X_{33}	0.496	.194	1.642
	X_{34}	-1.475	0.202	0.229
	X_{41}	0.454	0.207	1.574
	X_{45}	0.409	0.206	1.505
	X_{46}	0.086	0.029	1.090
	X_{47}	-0.058	0.019	0.944
9	X_{12}	0.440	0.123	1.553
	X_{13}	-0.262	0.142	0.770
	X_{16}	0.312	0.134	1.366
	X_{21}	0.038	0.020	1.039
	X_{32}	-0.055	0.024	0.947
	X_{34}	-1.126	0.217	0.324
	X_{41}	0.659	0.209	1.933
	X_{42}	-0.011	0.008	0.989
	X_{45}	0.501	0.267	1.651

Estimated coefficients of degree of trust in conversation with people at the workplace are not statistically significant in each case. In addition, estimated coefficients of degree of trust in stranger conversations are not statistically significant in many cases. On the one hand, estimated coefficients of degree of trust in the Internet, weekly/monthly magazines are statistically significant if failure probability is up to 2%. Otherwise, they are not statistically significant. On the other hand, if failure probability is more than 5%, estimated coefficients of degree of trust in e-mail or phone call with friends are statistically significant.

Effects of degree of trust in information source give us messages on sources we might provide information. For instance, given failure probability is a small, the more individuals trust in weekly/monthly magazines, the higher a probability which they tend to withdraw their deposit is. If a bank run occurred, then we would provide information for obstructing it. Unfortunately, because nobody collects such information regularly, we generally cannot grasp degree of trust in information sources.

Estimated coefficients of the number of friends or colleagues are only statistically significant and the values are positive in the extreme case that failure probability is 0.1% and 99%. On the other hand, the number of friends or colleagues who rumor failure of bank is statistically significant but the values are negative in almost cases.

The number of friends or colleagues and the number of friends or colleagues who rumor failure of bank may lead to image the chain of the rumors. However, from results in Table 4, the more individuals have the number of friends or colleagues who rumor failure of bank, the lower a probability which they tend to withdraw their deposit is. These results are opposite to the sign that we image at first, but these results would be important information when we conduct network analysis.

In only one case, estimated coefficients of the number of bank accounting are only statistically significant. It is found that the coefficients tend to be statistically significant if failure probability is higher. On the other hand, estimated coefficients of the number of recognition of Japanese deposit insurance scheme are statistically significant and the values are negative in all cases.

As Yada et al (2009) point out, if individuals correctly recognize Japanese deposit insurance scheme, the probability that they withdraw their deposits tends to be lower. In other words, this suggests having to make people understand the scheme.

If failure probability is more than 50%, estimated coefficients of gender are statistically significant; female tends to withdraw her deposit rather than the man after receiving information that failure probability is more than 50%. Estimated coefficients of age are statistically significant and the values are positive in half of cases, but the insistence may not be robust. No estimated coefficients of neither living area or rate of time-preference is statistically significant. Estimated coefficients of education and marriage status are statistically significant in half of cases. Then, it is found that the coefficients sift negative to positive values if failure probability is higher. In Takemura and Kozu (2009) estimated coefficients of annual income is not statistically significant, but in half of cases the coefficients are statistically significant and positive. In addition, estimated coefficients of debt are statistically significant and negative in half of cases. Furthermore, estimated coefficient of degree of risk aversion is statistically significant and negative in only one case, which failure probability is 5%.

It is very interesting that individual attributes like education and marriage status influence deposit-withdrawal behavior and by differences of the failure probability the effects are different, too.

4 A Proposal of Micro Financial Policy Tool

In section 3, we find some relationships between individual's deposit-withdrawal behavior, and economic and psychological factors in each failure probability. By using the results, we search for a cue of micro financial policy tool. In this paper, we roughly define micro financial policy as a policy taking into account various individual behaviors, not representative or averaged behavior.

As we mentioned in section 1, an approach based on macroeconomic model somewhat lacks flexibility. One main reason is that agent's behavior in the model is assumed to be symmetric. On the other hand, because agents' behaviors of our model in this paper are assumed to be asymmetric, an approach based on microeconomic model would have flexibility. For example, suppose that the government implements a policy. The policy efficiently works towards some citizens, but not toward the other citizens. An approach based on microeconomic model can clarify effects of policy more carefully than macroeconomic model. That is, by using an approach based on microeconomic model we can show a fine policy. We can clarify a policy that is more effective towards citizens who have a certain attribute in our approach.

Micro financial policy tool that we suggest needs two components; 1) an approach based on microeconomic model, and 2) network analysis. Fig. 14 shows concept of micro financial policy tool that we image.

For 1), as you saw in this paper, we need data on individual's psychological factors and economic behaviors related with a policy immediately or indirectly, and statistical method. About the former, it is difficult to collect such data on a large scale by mail-in survey or experiments survey because it is deeply related to the problem of privacy. Therefore, we rely on the Web-based survey as one social survey method by using such data. As we mentioned in section 2.2, accuracy of data collected from Web-based survey is inferior to accuracy of data collected from the other social survey, but the data would be useful. Especially, it is difficult to collect an accurate data about individual financial behavior by using either social method. Thus, it might be suitable to collect data from Web-based survey. Then, in repeating this survey, we can investigate the refinement of results. In addition, we can build individual decision-making model by incorporating into some psychological factors and the others' behaviors. For instance, we find that psychological factors affect individual's deposit-withdrawal behavior in section 3. Because such psychological factors are time-inconsistent,

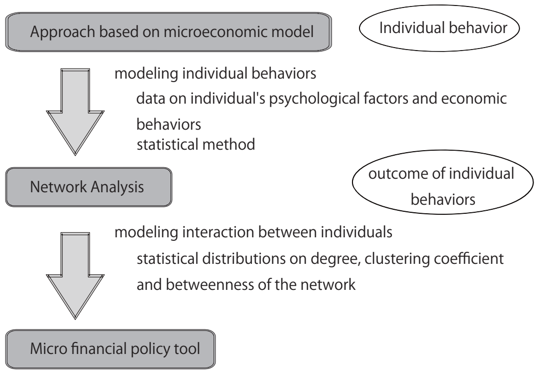

Fig. 14. Concept of micro financial policy tool

by grasping current situation statistically, we might be able to forecast outcomes of individual withdrawal-behaviors in the whole society if some shock occurred.

For 2), we need to carry out network analysis to express communication between individuals more richly. Here, a network represents a graph which consists of some vertexes (or nodes) and edges. In this graph, vertexes represent individuals or individual behaviors, and edges represent communication between individuals. It is important to represent how to communicate with outcome of individuals' decision-making one another. Since a network represents individuals' interaction visually, it is very useful. For example, network analysis presents way of bad news or good news spreading via what kind of route. Therefore, we need to know whether a real society is composed of what kind of network. For a long time, there are many studies on network analysis concerning with communication between individuals, but there are so few studies that use the real social network structure[14]. The reason is that there are few techniques to observe the social connection among individuals directly. So, we need a new technique to build a social network based on micro data. Ichikawa et al (2009, 2010) challenge to build a social network based on the data collected from our Web-based survey and a generic algorithm (GA). They will complete to build a network analysis based on data collected from Web-based survey in the near future.

By connecting a network analysis with individual behaviors based on microeconomic model, we can build richer behavioral model. Then, we will be able to provide one (micro) financial policy tool[15]. If insecurity information on a bank flowed to the society, we would be able to forecast timing of bank run and the scale and then show one material of method and policy to escape bank run

[14] Barabasi and Albert (1999) is representative study. Most studies on the social network assumes that the real social network has small world network and/or scale free network characteristics, and use some sort of virtual networks which does not exactly reflect the real social network.

[15] Professor Ukai named such a tool "Tsurugi." Refer to Ukai (2009) about details.

beforehand[16]. Even if bank run unfortunately occurred, we would provide one material of method to settle it.

For example, we will provide information that financial institution should prepare total amount of deposit in each branch if a bank run occurred. And, to settle a bank run, we would provide information that financial institutions and government should send facts and figures to what information source according to which timing.

5 Concluding Remarks and Future Work

In this paper, we refine the model in Takemura and Kozu (2009) and investigate relationships between individual's deposit-withdrawal behavior and factors behind them using micro data collected from a Web-based survey that we conducted in March 2009. As a result, we find some relationships between individual's deposit-withdrawal behavior, and economic and psychological factors. In Takemura and Kozu (2009) almost economic values are not statistically significant, but in this paper many of them are statistically significant and the signs are consistent with theoretical framework. In addition, we confirm that psychological factors influence individual deposit-withdrawal behavior, too. As interest finding, by differences of the failure probability, significant variables are different in each case. Especially, we confirm that the probability that they withdraw their deposits tends to be lower if individuals correctly recognize Japanese deposit insurance scheme. In other words, this suggests having to make people understand the scheme and we think that the education is an effective countermeasure to avoid a bank run.

By using the estimated results, we propose a micro financial policy tool. This tool consists of an approach based on microeconomic model and a network analysis, and we can provide more information on individual behaviors in the whole society. If insecurity information on a bank flowed to the society, we would be able to forecast timing of bank run and the scale and then show one material of method and policy to escape bank run beforehand. Even if bank run unfortunately occurred, we would provide one material of method to settle it. We will complete to build this tool in the near future.

Finally, we will briefly discuss future work. Some problems remain on this paper; reliability of data collected from the Web-based survey, some assumptions in this paper, and so on. In addition, building model cooperating into the relations, which is a network consisting of friends and colleagues has not successes yet. We will construct such a model in the future. Furthermore, we will reexamine degree of risk aversion and time-preference and intend to build a new behavior model.

[16] Of course, there is a possibility of not happening at all, too.

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