Modeling individuals' deposit-withdrawal behaviors after receiving information on financial turmoil

Toshihiko Takemura
Kansai University

Takashi Kozu
Ricoh Institute of Sustainability and Business

ABSTRACT

The purpose of this paper is to investigate the relationships between individuals' deposit-withdrawal behaviors and the factors behind them, using micro data collected from a Web-based survey conducted in March 2009. As a result, some relationships between individuals' deposit withdrawal behaviors and economic and psychological factors are found. For example, the probability of withdrawing deposits tends to be lower if individuals clearly understand the Japanese deposit insurance scheme. This suggests that education to make individuals know the scheme well enough may be an effective measure for avoiding bank runs. In addition, it is found that individuals' attributes such as educational backgrounds and marital status as well as differences in the probability of possible bank failure tend to influence deposit-withdrawal behaviors.

Keywords: depositor behaviors, psychological factor, communication, logistic regression analysis, Web-based survey

INTRODUCTION

Problems of subprime loans and the failure of Lehman Brothers became one trigger to a harsh economic blow not only to the United States, but also to most other countries as well. Many companies decreased their revenues and some went bankrupt. Bank runs and other financial panic occurred in the United States and in the United Kingdom. Japan is no exception as it faces the state of depression. Although the Japanese government has implemented various economic and monetary policies, people cannot necessarily accept that these policies work effectively. Using macroeconomic models, many economists discuss the effectiveness of economic and monetary policies that have to be deployed to achieve a recover from the state of depression. See, for example, Choe and Lee (2003), and Pathan, Skully and Wickramanayake (2008). An approach based on the macroeconomic model is effective in analyzing the economic impact to the whole economy, but most of the results have little flexibility and generally individuals' behaviors are not explicitly considered, just assuming a representative agent and analyzing data in an aggregated way. However, it may be doubtful whether or not the macroeconomic model can correctly capture individuals' behaviors in a panicky situation. This seems to be one of the limits of an approach based on the macroeconomic model when it is applied on an economy in a state of depression where finance transactions are very unstable. As one of the approaches that could overcome this limit, the authors try in this paper an approach based on a microeconomic model where the economic impacts on individuals and/or companies are explicitly analyzed. Also, an approach based on the microeconomic model is useful in the sense that it can adopt factors which cannot be built into a macroeconomic model. In the microeconomic model, the results of analysis could bear richer suggestions than the macroeconomic model.

In this paper, the authors assume a state of depression and apply a quantitative approach on individuals' deposit-withdrawal behaviors using a microeconomic model. In other words, they try to capture an individual behavior in a panicky situation by using the microeconomic model. Consequently, the authors can obtain a clue to understand a situation of financial panic like a bank run where many individuals withdraw their deposits almost at the same time. This paper can provide some information on how they can avoid bank runs and/or settle them when they actually occur. In sum, the authors hope that this paper will be able to explain a bank run mechanism to some extent and offer some implications to financial institutions and the government[1].

Many qualitative studies on bank runs and finance crisis exist, for example, Allen and Gale (2007), Shitter (2008), and Nagaoka and Takemura (2009). On the other hand, studies based on data analysis are new and challenging, and the accumulation of such studies is considerably few: Takemura and Kozu (2009), and Yada, et al (2009)[2].

Takemura and Kozu (2009) statistically analyzed individuals' deposit-withdrawal behaviors in Japan using micro data collected from a Web-based survey and clarified some factors that influence individuals' behaviors. It is suggested in the paper that banks and authorities have to pay attention to information sources of individuals which are frequently used and to a possibility that they could block the chain of information exchange for preventing a financial turmoil and avoiding avoid a unnecessary panic. Besides, they confirm that there are no statistical relationships between individuals' deposit-withdrawal behavior and economic variables such as annual income, amount of deposit and the number of accounting. Yada et al (2009) analyzed individuals' deposit-withdrawal behaviors using the same micro data as

[1] These studies are also important when researchers analyze the financial crises from the viewpoints of economics even when they do not intend to exercise any wide-scale simulation.

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

Takemura and Kozu (2009) applying data mining technique. Then, they clarified some factors that influence the behavior of individuals[3]. In addition, they estimated the total amount of deposit in each branch of a financial institution that should be kept if a bank run occurs.

In this paper, the authors attempt to refine the model in Takemura and Kozu (2009) using micro data collected from a Web-based survey that they conducted in March 2009, and investigate the relationships between individuals' deposit-withdrawal behaviors and some factors. By doing so, the authors suggest possible countermeasures whereby depositors will not draw out their entire deposits after receiving information on financial turmoil.

FRAMEWORK

Model and Statistical Method

Takemura and Kozu (2009) modeled individuals' deposit-withdrawal behaviors when they receive information with regard to financial turmoil using the framework of a logistic regression model[4]. In this paper, the authors attempt to refine the model.

Similarly, the authors build a model by a binary logistic regression equation, in which the explained variable is the probability that individuals withdraw their deposits after receiving information on financial turmoil. Explanatory variables are grouped roughly as follows: 1) degree of trust in information sources, X_1, 2) the number of correspondents i.e. friends or colleagues with whom individuals exchange information, X_2, 3) individual transactions with banks, X_3, and 4) individual's attributes, X_4. Instead of the frequency of communication used in Takemura and Kozu (2009), the authors use the number of correspondents. By using this factor, they try to analyze a process of information diffusion as to individual deposit-withdrawal behavior. This is one of the new challenges. As for other challenges, the authors use more sophisticated micro data rather than in Takemura and Kozu (2009).

If the probability of failure of the bank which an individual uses mainly, k (%) is set, the relationship between the explained variable and the explanatory variables is simply described as equation (1):

$$\text{Log}\ [p_k / (1-p_k)] = b_1X_1+b_2X_2+b_3X_3+b_4X_4 \qquad (1)$$

where p_k is the probability that the individual withdraws his/her deposit after receiving information on the probability of failure of his/her bank and b_j (j = 1,2,3, and 4) represent 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 b_j is positive (resp. negative), then individuals are apt to (resp. not to) withdraw all of their deposits after receiving information on the probability of failure of their bank. On the other hand, if a coefficient of a variable is zero, the factor does not affect individuals' deposit withdrawal behavior. A bank run will occur if a certain numbers of individuals withdraw their deposits, and such a situation is an undesirable for banks. Therefore, it is important to recognize the meaning of variables in equation (1) to understand the bank run mechanism.

In this paper, the model described by equation (1) incorporates not only economic variables, but also psychological ones in the decision-making process of depositors. It is assumed that depositors would be strongly affected by psychological

---

[3] Some individual attributes that influence the deposit withdrawal action are different even though Takemura and Kozu (2009) use and analyze the same data according to a different approach. The factors that influence deposit-withdrawal behaviors are somewhat different.

[4] The logistic regression model has been widely used to build 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.

factors if they encounter a financial panic situation such as a bank run. Microeconomic models are able to adapt some psychological factors. As psychological factors, the authors use degree of risk aversion, the time discount rate, and degree of trust on information sources.

Let us briefly explain here the methods and the processes to estimate the coefficients in equation (1) and to evaluate the fit of the model. In the estimation of the each coefficients in equation (1), the general maximum likelihood estimation method based on a binominal distribution is used generally, and computer software for statistical analysis is used in case the calculation of the estimations is too complex. In this paper, all the variables concerned with deposit-withdrawal behavior collected from the survey are incorporated into equation (1) in the first place, and then the "variable decreasing method" is applied. It is a method to search for a combination of variables that maximize the likelihood in equation (1) is applied deleting variables which do not have enough explanatory powers. The chosen variables are statistically significant ones which maximize the likelihood[5].

Next, the fitness and the validity of the model are evaluated by running the Hosmer-Lemeshow test and using a positive distinction rate, which measures the fit of the model. Please see Hosmer and Lemeshow (2000) for the details of the test.

Data Set

The environment of the social survey such as using post mails, face to face interviews and telephone calls has been changing in recent years and the difficulty of such surveys have been increasing gradually in Japan[6]. In other words, asking respondents for cooperation in such surveys become more and more difficult. Therefore, in spite of many researchers' efforts, most of them fail to achieve acceptable response rates in many cases. On the other hand, the Web-based survey (Internet survey) is gaining attention as a new approach in the field of marketing research[7]. The Japan Institute for Labour Policy and Training (2005) suggests that it is not necessarily undesirable to use a Web-based survey if the aim of the survey is to offer judgmental materials that are useful for individual and organizational decision makings. Of course, the authors must discuss the accuracy of the survey but unfortunately the authors cannot make comparison as there is no similar survey other than the Web-based surveys. In the future, the authors need to expand the scope of the utilization of the data collected from a Web-based survey[8].

In this paper, the authors use data collected from a Web-based survey that they conducted in March, 2009[9]. The subjects of this survey are Japanese depositors who have more than one bank account and more than four correspondents with whom they

---

[5] During the process, if there are variables with no influence or have statistically no relations with deposit-withdrawal behavior, they would be eliminated from equation (1) by turns.

[6] The Japan Institute for Labour Policy and Training (2005) point out that in social survey there are various environmental changes such as decrease in the recovery rate, and increase in the refusal rate. In addition, nowadays, a list of names utilized in sampling is not easily available because the using of the list is limited in Japan.

[7] Couper (2000) reviews issues and approaches to Web-based surveys.

[8] For example, Ohsumi (2002) gives some suggestions on the limit and the possibilities of Web-based surveys in the future. Hoshino (2010) discusses adjustment of selection bias in data of between mail-in survey and Web-based survey and develops adjustment tool for the selection bias.

[9] You can see this survey slips by accessing to Website of Research Institute for Socionetwork Strategies, Kansai University, Japan (RISS).
URL: http://www.kansai- u.ac.jp/riss/en/shareduse/database.html.

frequently communicate. Here, let us briefly explain the reason why we target the individuals who have more than four correspondents. To build a network which represents the interactions between individuals, the authors need to know statistical distributions on degree, the clustering coefficient, and betweenness of the network[10]. Because it is generally expected that the degrees of the network are more than four, the same condition is imposed. In addition, samples of this survey are arranged according to three dimensions; gender, age and living area in Japan[11].

The aim of this survey is to capture individual deposit-withdrawal behavior from the viewpoints of economics, psychology and social networks. This survey asks more than 50 question items such as gender, annual income, degree of trust in information sources, degree of risk aversion, and the number of correspondents. This survey includes 1365 respondents and the sample size excludes those who answered in an obviously contradicted way and those who fail to answer some questions.

Individuals' deposit withdrawal behavior

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

p_k = 1 if he/she withdraws his deposit
= 0 otherwise,

where p_k represents the probability that an individual withdraws his/her deposit after receiving information on the probability of failure of his/her bank.

In this survey, questions on deposit-withdrawal behavior are asked, assuming nine different failure probabilities of the depositor's bank i.e. k = 0.1, 0.5, 1, 2, 5, 20, 30, 50, and 99 (%). Figure 1 shows distributions for deposit-withdrawal behavior. When k = 5%, almost half of those answered intend to withdraw their deposits. It seems that a relation between failure probability and the ratio of individuals withdrawing deposits show an S shaped curve. The ratio of individuals withdrawing deposits is about 14.0% even if k = 0.1%, while the ratio of those do not withdraw deposits is about 7%, even when k = 99%. In the former case, many respondents answered that they will withdraw their deposits if there is a very little failure probability (i.e. as far as k > 0). On the other hand, in the latter case, many respondents answered that they will never withdraw their deposits because the deposits are guaranteed by the Japanese deposit insurance scheme.

Degree of trust in information sources

In Takemura and Kozu (2009), the authors found that some degrees of trust in information sources influence an individua1's deposit-withdrawal behavior. In this survey, questions about the degree of trust in information sources for good news and bad news are asked separately. And, as an information source, they use TV, X_{11}, newspaper, X_{12}, Internet, X_{13}, conversations with neighbors, X_{14}, conversations with people at the workplace, X_{15}, e-mail or phone calls with friends, X_{16}, weekly/monthly magazines, X_{17}, and conversations with strangers, X_{18}.

---

[10] In Ichikawa et al (2010), the researcher's challenge was to rebuild a social network based on the data collected from Web-based surveys with a generic algorithm (GA) and to discuss employing the rebuilt network to a social simulation.

[11] To arrange three axes, the authors 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 registration on the 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.

Distributions for the degree of trust in information sources are shown in Figure 2. The degrees of trust in information sources are different in each source. In addition, as an overall tendency, no great disparity in degree of trust is found between good news and bad news.

In this paper, as the authors take the probability of an individual's bank failure as the information on financial turmoil, they use degree of trust in information sources in bad news.

The number of correspondents as to information exchange

Information spreads through not only mass media such as TV, newspapers, and the Internet, but also through individual communications within closed circles. Individual communications play important roles in depositors' decision-making as in game theory. When the authors analyze the depositors' decision-making using micro data, they need to obtain data on the number of correspondents, i.e. friends or colleagues, with whom the depositor frequently exchanges information. In this survey, both the number of correspondents with whom depositors exchange information, X_{21}, and the number of those who may influence the depositors' deposit-withdrawal behaviors, X_{22} are asked.

The distribution of X_{21} is shown in Figure 3. The average (median) is 9.39 (resp. 7).

Figure 4 shows the distribution of the ratio of possible number of correspondents who might hear a rumor of a bank failure. It is noted that respondents' ratios exceed 100 (%) because in some answers the numbers are exceeding those of the correspondents. It might be because those who depositors do not exchange information frequently are also included here. Thus, the authors uniformly convert the ratio into 100% in such cases.

The average (median) here is 43.18 (resp. 37.5) %.

Transactions of individuals with banks

To capture the transactions of individuals using banks, four variables are used in this paper; the number of bank accounts, X_{31}, total amount of deposit, X_{32}, type of main bank, X_{33} and understanding of the Japanese deposit insurance scheme, X_{34}. In this survey, questions are asked on the number of bank accounts, amount of bank account with most deposits, type of main bank and understanding of the Japanese deposit insurance scheme.

The number of bank accounts is a substitute for individuals who intend to disperse their deposits. The total amount of deposits is needed in order to judge whether or not the deposits are protected by the Japanese deposit insurance scheme. Table 1 and Figure 5 show elementary statistics on the number of bank accounts and distribution for the total amount of deposits, respectively. The median and the mode of the total amount of deposit is 1-2 million yen and less than one million yen, respectively.

The type of individuals' banks is defined by using the following indicator function:

X_{33} = 1 if individual uses Japanese mega bank including Yucho bank as their mostly using bank,

= 0 otherwise,

where Japanese mega banks are Tokyo Mistubishi UFJ bank, Mitsui Sumitomo bank, Mizuho bank and Resona bank. Figure 6 shows the distribution.

In Yada et al (2009), they found that the knowledge of the Japanese deposit insurance scheme influences individuals' deposit-withdrawal behaviors. They pointed out that this variable is an important factor. In the Japanese deposit insurance scheme, a deposit up to 10 million yen is guaranteed as the upper limit even if banks fail. Figure 5 shows that the scheme covers 90.2% of respondents. Though their deposits are guaranteed by the scheme, as you see in Figure 1, all of them (90.2%) are going to withdraw their deposits after receiving information with regard to financial turmoil.

This may imply that they do not clearly understand the Japanese deposit insurance scheme. Therefore, the authors pick up the knowledge of the Japanese deposit insurance scheme as one of the variables. In this paper, the knowledge of the Japanese deposit insurance scheme is defined as follows:

X_{34} = 1 if depositor has knowledge of Japanese deposit insurance scheme
= 0 otherwise.

Figure 7 shows the distribution of depositors' knowledge on the Japanese deposit insurance scheme. In a question on the knowledge of the Japanese insurance scheme, it is asked whether a respondent takes the scheme into account when they make decisions on bank account withdrawal. 52.8% of respondents answered that they know the scheme but do not take it into account when they decide their actions. It should be noted that such respondents are regarded in this paper that they do not clearly understand the scheme and therefore they are categorized as "no understanding" in Figure 7. This implies that the system is meaningless if depositors do not correctly understand it.

Individual's attributes

As variables for individuals' attributes, the authors use gender, X_{41}, age, X_{42}, living area in Japan, X_{43}, education, X_{44}, marital status, X_{45}, annual income, X_{46}, and amount of debt, X_{47}. By arranging the population by age group and prefectural divisions of the MIC in Japan, they can obtain the data on gender, age and living area in Japan. See footnote 11). Figures 8-11 show the distributions for education, marital status, annual income and amount of debt, respectively. . The annual income of 19% of respondents is less than five hundred thousand yen and the median value is 2-2.5million yen partly because this sample includes housewives (20.9%) and students (4.5%) and thus the median value stays low. Regarding debt, about 73% of respondents answered that they have no debts[12].

As the psychological factors used in economics, the authors have degree of risk aversion, X_{48}, and the time discount rate, X_{49}. In this paper, they apply the degree of absolute risk aversion used in Cramer et al (2002). The absolute risk aversion (RA) is calculated by the following equation:

$$X_{48} = [aZ-r]/[1/2(aZ^2-2aZ+r^2)] \qquad (2)$$

where Z, a and r represent lottery winnings, winning probability, and the price of the lottery, respectively. X_{48} would be positive (negative) if the individual is risk averter (lover), and X_{48} would be zero if he/she is risk neutral. To calculate X_{48} by using equation (2), given Z and r, the authors need to obtain the coefficient a. In this survey, it is asked how much respondents would pay for a lottery ticket given r = 1/100 and Z = 100,000 (yen). Figure 12 shows the distribution with regard to X_{48} calculated by equation (2). Almost all respondents are risk averse. The average and median is 0.001248 and 0.001399, respectively.

Regarding the time discount rate, in this survey the respondents are asked to compare the cases of 10,000 yen investment for 1 month and 13 months with 8 different interest rates and to choose one of them. The authors calculated the time discount rate based on the information obtained by the survey. Figure 13 shows the distribution for the time discount rate. The average and median is 11 (%) and 8 (%), respectively.

See Ohtake and Tsutsui (2005) for the actual process of calculating degree of risk aversion and the time discount rate.

ESTIMATED RESULTS

Here, the authors estimate the coefficients in equation (1) by running the

[12] There may be some respondents who answer zero even if they have debt because this question is very naive in content. Thus, the number of respondents with no debt may be exaggerated.

variable decreasing method with likelihood ratio. In this paper, PASW Statistics ver.18 is used as computer software for statistical analysis. They used nine different probabilities of depositors' bank failure and 23 explanatory variables.

Tables 2 and 3 show the statistics of the used tests and the estimated coefficients in equation (1), respectively.

From results in Table 2, the authors evaluate the fit of the models. All models are 5% or more significant and in addition it can be said that all models are also valid because the positive distinction rate turns out to be between 56% and 93%.

From Table 3, with the different probabilities of bank failure, the variables that finally survived through the processes of the variable decreasing method with likelihood ratio are different. Here, the authors briefly summarize differences among the results.

The estimated coefficients of the degree of trust in communications with people at the workplace are not statistically significant in every case. In addition, the estimated coefficients of the degree of trust in communications with strangers are not statistically significant in most of the cases. On the one hand, the estimated coefficients of the degree of trust in the Internet, and weekly/monthly magazines are statistically significant if the failure probability is up to 2%. Otherwise, they are not statistically significant. On the other hand, if the failure probability is more than 5%, the estimated coefficients of degree of trust in an e-mail or in a phone call with correspondents are statistically significant.

The effects of the degree of trust in the information sources provide us with the messages that, when the assumed failure probability is low, the more individuals trust in weekly/monthly magazines, the higher the probability that they will withdraw their deposit. If a bank run occurs, then it would be better to provide information to obstruct the process but unfortunately the degrees of trust in information sources cannot be grasped in general because such information is not collected regularly and thus we cannot take such reaction.

The estimated coefficients of the number of correspondents are statistically significant and the values are positive in the extreme cases where the failure probabilities are 0.1% and 99%. On the other hand, the possible number of correspondents who might hear the rumors of a bank failure is statistically significant, but the values are negative in almost all cases.

When the authors look at the number of correspondents with frequent contacts and the possible numbers of correspondents who might hear a rumor of a bank failure, they may be tempted to assume a chain of the rumors. However, Table 3 indicates that, the higher the possible number of correspondents who might hear a rumor of a bank failure, the lower the probability that they will withdraw their deposits. This result is contradictory to our instinct but may contain important information for the researchers who conduct network analyses.

In only one case, the estimated coefficients of the number of bank accounting are statistically significant. The coefficients tend to be statistically significant if the failure probability is higher. On the other hand, the estimated coefficients of the numbers of people who have the knowledge of the Japanese deposit insurance scheme are statistically significant and the values are negative in all cases.

As Yada et al (2009) pointed out, if individuals clearly understand the Japanese deposit insurance scheme, the probability that they withdraw their deposits may tend to be lower. Thus the result may suggest efforts to make people better understand the scheme would be useful in avoiding bank runs.

When the failure probability is more than 50%, the estimated coefficients of gender are statistically significant; females tend to withdraw their deposits rather than men. The estimated coefficients of age are statistically significant and the values are positive in half of the cases, but the result may not be robust enough. No estimated coefficients of either living area or the time discount rate are statistically significant. The estimated coefficients of education and marital status are statistically significant in half of the cases. The coefficients shift from negative to positive if the failure probability is higher. In Takemura and Kozu (2009), the estimated coefficients of annual income were not statistically significant, but the coefficients are statistically significant and positive in half of the cases this time. In addition, the estimated coefficients of debt are statistically significant and negative in half of the cases. Furthermore, the estimated coefficient of degree of risk aversion is statistically significant and negative in only one case, when the failure probability is 5%.

The result show that the individual attributes such as education and marital status influence deposit withdrawal behavior as well as differences of failure probability.

SUMMARY AND FUTURE WORK

This paper refines the model of Takemura and Kozu (2009) and investigates the relationships between individuals' deposit-withdrawal behaviors and some factors behind using micro data collected from a Web-based survey that the authors conducted in March 2009. As a result, some relationships are found between individuals' deposit-withdrawal behaviors, and economic and psychological factors. In Takemura and Kozu (2009), most economic values were not statistically significant, but in this paper many economic values are statistically significant and the results are consistent with the theoretical frameworks. In addition, it has found that psychological factors have influence on the deposit-withdrawal behavior. Also, using the different probabilities of possible bank failure, it has found, interestingly, that significant variables differ in all cases. In particular, the probability that depositors will withdraw their deposits is lower if individuals correctly understand the Japanese deposit insurance scheme. This may suggest that people need to understand the scheme correctly and therefore education could be an effective measure for avoiding bank runs.

Finally, let us briefly explain future works. Some problems still remain, such as reliability of data collected from the Web-based survey, and some assumptions in the paper. The authors would like to improve the model hereafter. Especially we believe the degree of risk aversion and the time discount rate should be reexamined in order to build a new behavioral model.

AKNOWLEDGE

This work was supported by "a Promotion Project for Joint Research between the Humanities and Social Science" from the Ministry of Education, Culture, Sports, Science and Technology, Japan (MEXT), 2008-2009 and "a Promotion Project for Distinctive Joint Research" from MEXT, 2010-.

We are thankful to participants of the Academic and Business Research Institute Conference Las Vegas 2010 and anonymous referees for variable comments.

REFERENCE

Allen, F., Gale, D. (2007): Understanding Financial Crises, Oxford University Press.

Choe, H., Lee, B. S. (2003): Korean Bank Governance Reform after the Asian Financial Crisis. Pacific-Basin Finance Journal, Vol.11, 483-508.

Couper, M. P. (2000): Web Surveys: A Review of Issues and Approaches. Public Opinion Quarterly, Vol.64, 464-494.

Cramer, J. S., Hatog, J. N. Jonker, Van Praag, C. M., (2002): Low Risk Aversion Encourages the Choice for Entrepreneurship: An Empirical Test of a Truism. Journal of Economic Behavior and Organization, Vol.48, 29-36.

Hoshino, T. (2010): Adjustment of Selection Bias in Web Survey Data - Application to a Survey of Behavioral Economics. RCSS Discussion Paper Series, No.97.

Hosmer, D. W., Lemeshow, S. (2000): Applied Logistic Regression (2nd edtion). Wiley-Interscience Publication.

Ichikawa, K., Takemura, T., Murakami, M., Minetaki, K., Maeda, T. (2010): Social Network Rebuilder: A Tool to Estimate Social Network toward Bank Run

Simulation. RCSS Discussion Paper Series, No.91.
Nagaoka, H., Takemura, T. (2009): Case Studies of Bank Run in Financial Institutions: Suggestion from the Viewpoint of Risk Management. Selected Proceedings of the Second International Conference on Social Science (Social Sciences Research Society), Vol.5, 27-42.
Ohsumi, N. (2002): Internet Surveys : A Review of Several Experimental Results : Applying Data Science Approach to the Exploration of Internet Surveys (Reviews: Behaviormetrics in the 21st Century). The Japanese Journal of Behaviormetrics, Vol.29, No.1, 20-44.
Ohtake, F., Tsutsui, Y. (2005): Measurement of Risk Aversion: Experiment 2004.3 in Osaka University. http://www2.econ.osaka-u.ac.jp/coe/project/project.html
Pathan, S., Skully, M., Wickramanayake, J. (2008): Reforms in Thai Bank Governance: the Aftermath of the Asian Financial Crisis. International Review of Financial Analysis, article in Press.
Shiller, R. (2008): The Subprime Solution: How Today's Global Financial Crisis Happened, and What to Do about It. Princeton University Press, N.J.
Takemura, T., Kozu, T. (2009): An Empirical Analysis on Individuals' Deposit withdrawal Behavior's Using Data Collected through a Web-based Survey. Eurasian Journal of Business and Economics, Vol.2, No. 4, 27-41.
The Japan Institute for Labour Policy and Training (2005): Can the Internet Survey Be Used for the Social Survey?: A result by Experiment. Reports on Labour Policy, No.17.
Yada, K., Washio, T., Ukai, Y., Nagaoka, H. (2009): Modeling Bank Runs in Financial Crises. The Review of Socionetwork Strategies, Vol.3, No.2, 19-31.

Figures and Tables

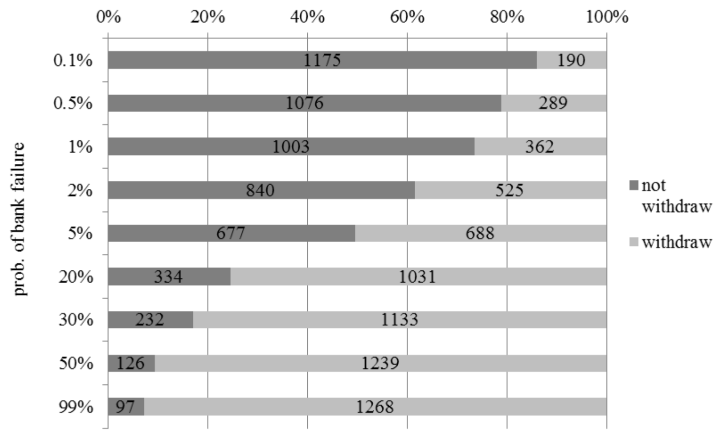

Figure 1: Distribution for deposit-withdrawal behavior

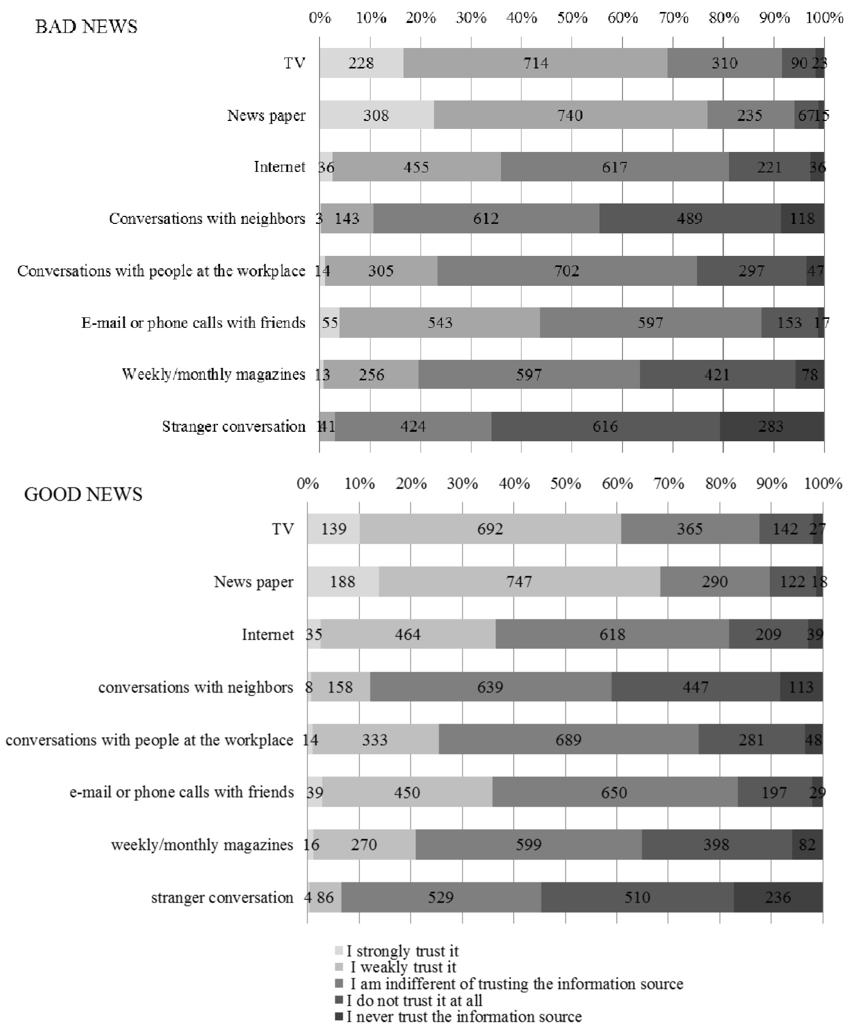

Figure 2: Degree of trust in information sources

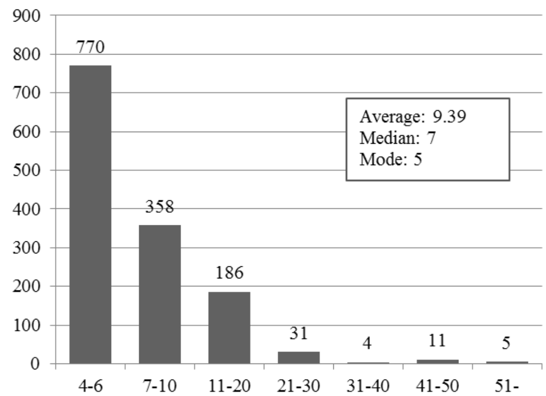

Figure 3: Distributions for the number of friends or colleagues exchanging information

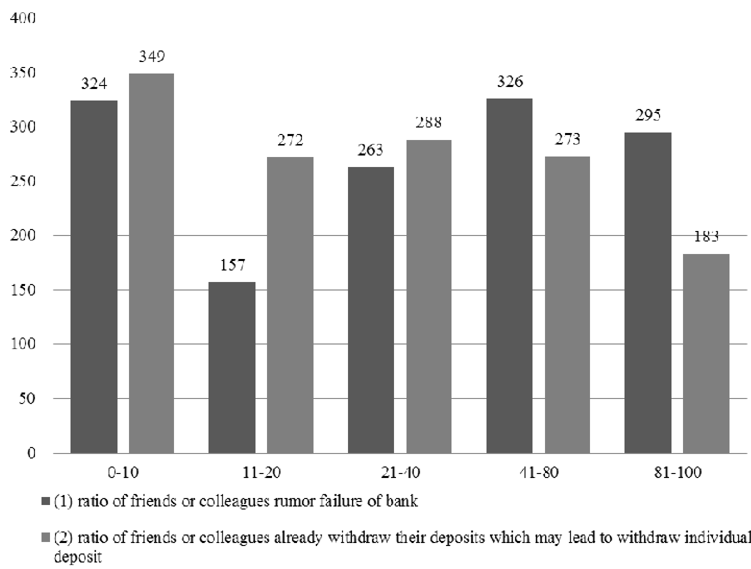

Figure 4: Distributions for the number of friends or colleagues

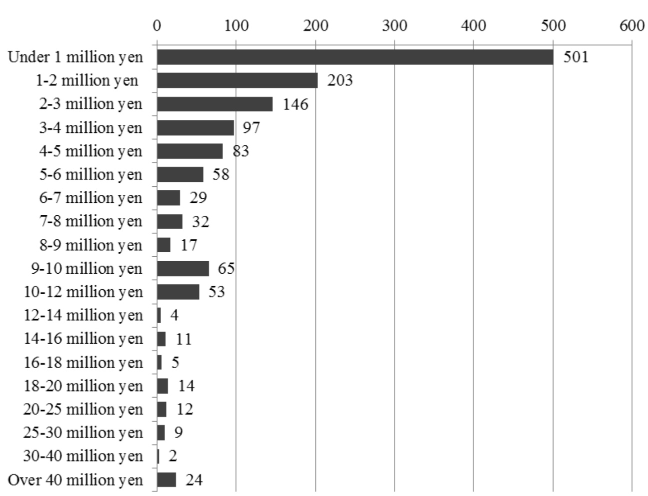

Figure 5: Distribution for total amount of deposit

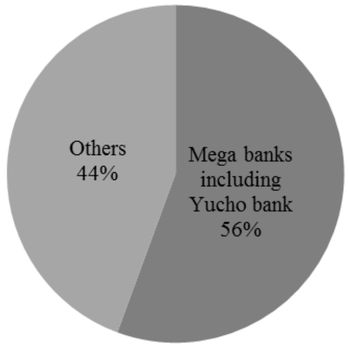

Figure 6: Distribution for individuals using main bank

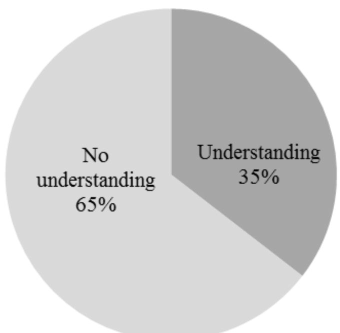

Figure 7: Distribution for depositors understanding Japanese deposit insurance scheme

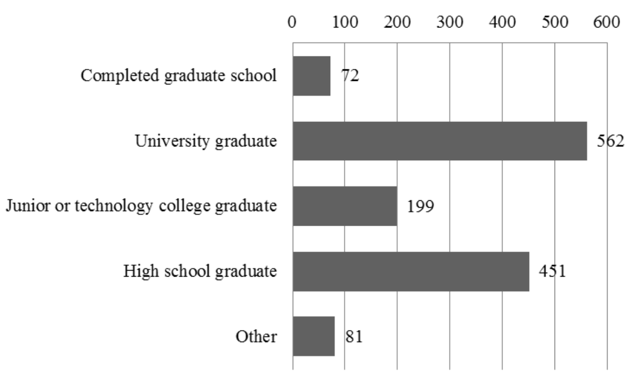

Figure 8: Distribution for education

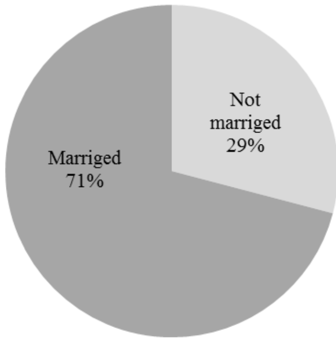

Figure 9: Distribution for marriage status

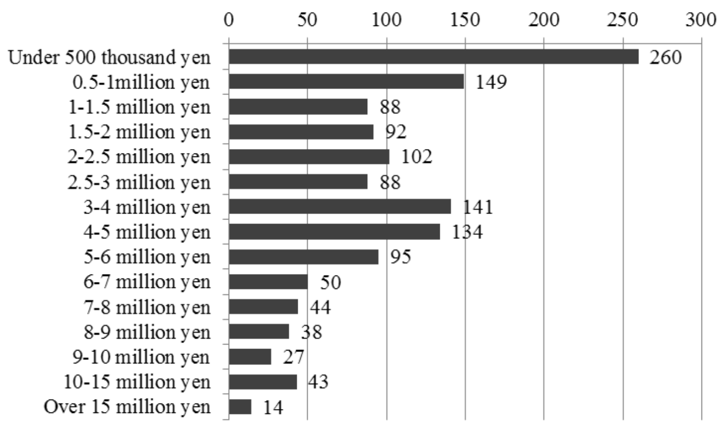

Figure 10: Distribution for annual income

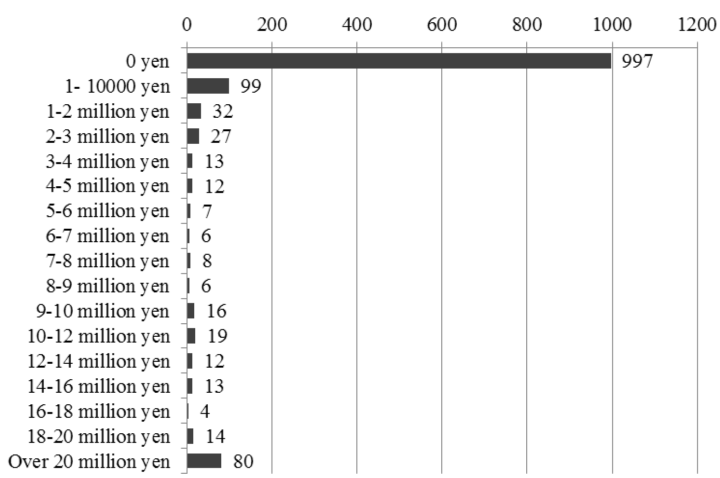

Figure 11: Distribution for debt

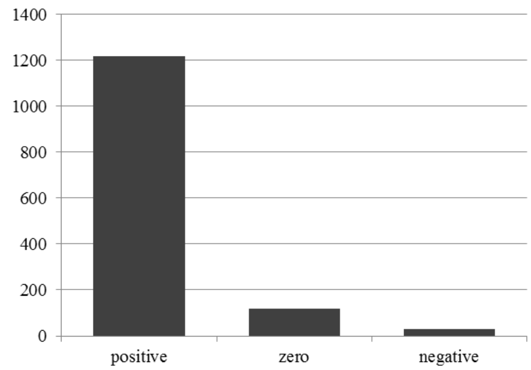

Figure 12: Distribution for degree of risk aversion

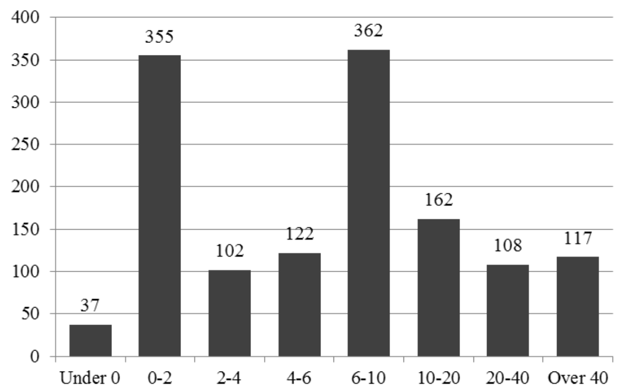

Figure 13: Distribution for time discount rate

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

Table 2: Summary of statistics

Case	-2 Log likelihood	Cox-Snell R^2	Nagelkerke R^2	Chi 2	Prob.	Positive distinction 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

Table 3: Summary of estimated results

Case	B		Standard error	Exp(B)	Case	B		Standard error	Exp(B)
1	b_{12}	-0.202	0.099	0.817	2	b_{12}	-0.102	0.078	0.903
	b_{13}	-0.141	0.107	0.869		b_{13}	-0.195	0.090	0.823
	b_{14}	-0.142	0.106	0.867		b_{14}	-0.165	0.089	0.848
	b_{17}	0.263	0.112	1.301		b_{17}	0.266	0.094	1.305
	b_{21}	0.006	0.004	1.006		b_{22}	-0.026	0.011	0.975
	b_{22}	-0.038	0.018	0.963		b_{34}	-0.379	0.146	0.685
	b_{34}	-0.337	0.173	0.714		b_{44}	-0.127	0.055	0.881
	b_{42}	0.012	0.006	1.012					
	b_{44}	-0.242	0.066	0.785					
	b_{45}	-0.355	0.199	0.701					
3	b_{11}	-0.128	0.076	0.880	4	b_{13}	-0.160	0.063	0.852
	b_{13}	-0.156	0.079	0.855		b_{17}	0.101	0.069	1.106
	b_{17}	0.116	0.084	1.123		b_{22}	-0.002	0.002	0.998
	b_{22}	-0.013	0.007	0.987		b_{32}	0.026	0.014	1.026
	b_{34}	-0.455	0.134	0.635		b_{34}	-0.531	0.122	0.588
	b_{45}	-0.200	0.118	0.819		b_{44}	-0.123	0.047	0.884
	b_{46}	0.037	0.016	1.037		b_{46}	0.039	0.016	1.040
5	b_{14}	-0.099	0.071	0.906	6	b_{12}	0.190	0.068	1.209
	b_{16}	0.130	0.066	1.139		b_{16}	0.155	0.080	1.167
	b_{22}	-0.008	0.005	0.992		b_{18}	-0.117	0.083	0.890
	b_{34}	-0.515	0.117	0.598		b_{22}	-0.007	0.004	0.993
	b_{42}	0.007	0.004	1.007		b_{33}	0.274	0.129	1.316
	b_{45}	-0.301	0.138	0.740		b_{34}	-0.806	0.133	0.447
	b_{46}	0.050	0.015	1.051		b_{42}	0.006	0.004	1.006
	b_{47}	-0.019	0.013	0.981		b_{46}	0.044	0.018	1.044
						b_{47}	-0.029	0.014	0.972
						b_{48}	-8020.2	6215.6	0.000
7	b_{12}	0.210	0.082	1.234	8	b_{11}	0.230	0.105	1.259
	b_{14}	-0.232	0.102	0.793		b_{14}	-0.243	0.136	0.784
	b_{16}	0.282	0.099	1.326		b_{16}	0.280	0.129	1.323
	b_{22}	-0.005	0.003	0.995		b_{22}	-0.002	0.001	0.998
	b_{31}	0.066	0.038	1.069		b_{33}	0.496	0.194	1.642
	b_{33}	0.280	0.150	1.323		b_{34}	-1.475	0.202	0.229
	b_{34}	-1.183	0.154	0.306		b_{41}	0.454	0.207	1.574
	b_{42}	0.009	0.004	1.009		b_{45}	0.409	0.206	1.505
	b_{44}	0.090	0.064	1.094		b_{46}	0.086	0.029	1.090
	b_{47}	-0.035	0.014	0.965		b_{47}	-0.058	0.019	0.944
9	b_{12}	0.440	0.123	1.553					
	b_{13}	-0.262	0.142	0.770					
	b_{16}	0.312	0.134	1.366					
	b_{21}	0.038	0.020	1.039					
	b_{32}	-0.055	0.024	0.947					
	b_{34}	-1.126	0.217	0.324					
	b_{41}	0.659	0.209	1.933					
	b_{42}	-0.011	0.008	0.989					
	b_{45}	0.501	0.267	1.651					