When do people visit a doctor?*

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Running Title: When visit a doctor?

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Abstract

We examine the length of time between when an individual feels sick and when he/she visits a doctor using survival analysis to capture the dynamic aspects of this behavior. If the disease is light, actions such as OTC medicine or sick leave are alternatives to visiting a clinic or a hospital immediately. The timing of the visit depends only the person's decision, not on a doctor's, so we can limit discussion to the effect of ex-post moral hazard excluding physician induced demand. Participants were asked to keep a log of illness-related behavior such as dates of episodes, subjective symptoms, sick leaves, and medical treatment at hospitals. Neither the copayment rate nor access cost had a significant effect on the behavior of visiting a doctor, whereas available alternatives delay the timing of a visiting. Severe symptoms and fever hastened the time. The results suggest that the traditional argument about ex-post moral hazard is somewhat misleading.

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Key Words: health care demand, ex-post moral hazard, copayment rate, survival analysis.

1 Introduction

This paper aimed to investigate the behavior of those feeling sick but who did not consult doctors. If the disease is light, alternatives such as OTC medicine or sick leave are available and they do not necessarily visit a hospital or a clinic(1) right away. Because the timing when they visit depends on their decision, not on a doctors', we can limit the discussion to the pure effect of ex-post moral hazard excluding physician induced demand. Then, what determine whether a person consult a doctor or not? Does the copayment rate of public health insurance affect the behavior? This paper considers these issues.

The Koizumi Cabinet is trying to advance structural reform and to restructure the public medical insurance system as one element of this reform. One of measures taken was to increase the copayment rate to better balance the budget of the National Health Insurance scheme. The underlying logic is based on the presence of ex-post moral hazard, or response of medical care cost to copayment rate. In the last few years a considerable number of empirical studies have been made on this price elasticity. However, there is little agreement as to magnitude of the response of Japanese medical expenses partly because the data might not provide enough variations in copayment rate. One question which we consider in this paper is the magnitude and, first of all, whether the copayment rate affects doctor visiting behavior.

In the last few decades a considerable number of empirical studies have been made, such as a series of research by RAND [1], on the demand for medical services. The relationship between the copayment rate and the demand for medical services, or price elasticity, has also been the subject

(1)Since Japanese public health insurance system does not have GP system, people can visit a hospital or a clinic, and visiting a doctor is considered as the same thing as visiting a hospital or a clinic.

of controversy. But as the physician induced demand hypothesis emphases, medical expenditure or the number of hospital visits might not be determined only by the patients, who consume medical service, because they generally do not have medical knowledge or the ability to judge the situation; it may be natural then that the decisions for the consumption of medical service are to some extent transferred to physicians. This means that how much medical service to consume depends not only on the decisions by the patients. Therefore, when we consider policy to control the behavior of patients, we must also analyze the behavior controlling the effect of physicians ([2] , [3]). This paper focuses on the initial contact of patients with physicians, such as the timing of starting going to hospital or hospital choice. If the decision made only by the patient was not affected by the copayment rate, the policy should intervene in the relationship of the patients and the physicians, or decision making of the physicians.

As the literature suggests, the decision of starting going to hospital can be divided to two phases ([4], [3]). The first phase is whether to go to hospital/clinic or not, and the second phase relates to which hospital/clinic to go. This model was analyzed empirically using a nested multinomial logit model (NMNL). But it is difficult to encompass the dynamic aspect of the decision making using simple discrete choice models, which implicitly assume that people decide to go to hospital or not at one time. Rather, decisions to visit hospital are sequential and depend on what happened yesterday or what is expected to happen tomorrow [5]. This paper focuses on the first phase employing duration analysis and using diary data, while the second phase is examined in Bessho and Ohkusa [6].

This paper is organized as follows. In Section 2 the data used in this paper is presented. We describe the econometric specification in Section 3 and Section 4 provides the estimation result.

Section 5 concludes.

2 Data description

Data sets used in this paper are based on a survey done in May 2001 in Tokyo Metropolitan areas (Tokyo, Kanagawa, Saitama, and Chiba) and the Kansai area (Osaka, Kyoto, Nara, Hyogo, Shiga, and Wakayama). This survey was implemented through a research company with which the sample households contract[(2)]. The number of distribution is 1300, that of collection is 1249.

The survey consists of Household Cards, Individual Cards, and Illness-related Behavior Record Cards. Homemakers filled in the Household Cards and members who were above 20 but below 69 years old wrote in the Individual Cards. Homemakers were also asked to keep logs of their household members' illness-related behavior from May to November 2001. Because the Illness-related Behavior Record Cards are diary-type, we can track occurrence and change of their symptoms and retrospective bias is quite small. We compare ratios of who feel sick with the National Livelihood Survey conducted in June, 2001. Since the results of the National Livelihood Survey show the ratios of who feels sick during several days of June, the ratios in the first week of June are calculated from our data sets. The results are shown in Table 1. The ratios are almost same for middle-aged female, but those of our data sets for aged people and male are smaller than those of National Livelihood Survey. The reason of difference of the ratios may be definition of "sickness", because the survey used in this paper focus on acute light illness as noted below.

[(2)]The households were randomly selected, but the research contract may yield sample selection bias.

The survey focus on acute light illnesses[(3)]. The reason we focus on acute light illness is as follows. First, if illnesses are light, alternatives such as OTC medicine or sick leave are available and they do not necessarily visit a hospital or a clinic right away, and the timing when they visit depends on their decision. Second, since most private health insurance in Japan do not cover light illnesses which this survey covers, we can shed light on public health insurance and need not take private health insurance into account. Therefore, to pick up acute light illnesses is appropriate to investigate pure effect of ex-post moral hazard. For this end, we drop such episodes where the number of days to go to a hospital is more than 30, for they may be chronic illness.

The Household Cards contain information on demographics and many kinds of health status. Individual Cards contain details on employment, income, health insurance, educational background, and preventive behaviors. Participants in the survey were questioned whether or not they take preventive behaviors listed in the Cards. Individual Cards also asked some questions from which the rate of risk aversion and time preference rate could be derived. Illness-related Behavior Record Cards contain information on medical care utilization. The logged behavior includes dates of illness episodes, histories of subjective symptoms, of sick leaves, and of medical treatment at hospitals. The length of periods from the day when members of households feel ill to the day when they go to hospitals for the first time or recover can be calculated using this data.

[(3)] To put it concretely, the sample households were asked to keep logs of illnesses, which contain cold, flu, hay fever, stomachache, headache, menstrual cramps, stiff neck, backache, constipation, food poisoning, conjunctival inflammation, glue ear, eye fatigue, athlete's foot, atopic dermatitis, insect bites, heat rash, urtication, physical damage, burn injury, bruise, sprain, piles, body odor, fatigue, excessive sensitivity to cold and cabin fever.

Copayment rates are calculated as follows. In 1961, Japan completed compulsory public health insurance with coverage for all residents, and each Japanese must enroll one of public health insurances according to one's job or other characteristics. Thus the copayment rate is exogenous for each individuals. Individual Cards asked the copayment rates that people faced, but those who are covered by National Health Insurance (*Kokumin Kenko Hoken*), which is one of public health insurances, were not asked that question. The copayment rate of National Health Insurance for working people is usually 30 percent of treatment fees paid to medical institutions under this medical insurance system, but that of the retirees covered by this insurance is 20 percent. Since the survey does not contain data of employment histories, we calculate the copayment rates of those covered by National Health Insurance using gender and age information. The copayment rate of males whose age is above 60 is set to 20 percent, and that of the others covered by National Health Insurance is 30 percent. Those who are covered by National Health Insurance and whose age is above 60 occupy 12.6% of those who became sick during the sample period, that is, whose records exist on the Illness-related Behavior Record Cards. From another point of view, they are 11.7% of episodes[(4)] which we used estimation below. These ratios seem not too large. Considering the existence of these benefits for high-cost medical care (*Kogaku-ryoyohi*) or additional benefits (*Fuka-kyufu*), it is very difficult to calculate the effective copayment rate for each episode. However it is also questionable whether all people know the effective copayment rate when they feel sick because of the complexity of the system. Therefore to calculate the copayment rate as above has some legitimacy. It also must be noted that we

[(4)]We call the sequence of the logs from the time when an individual feels sick to the time when he/she recovers as an 'episode'. In our data some people had several episodes during the survey period.

were unable to use information about private health insurance which household members might have bought. As noted before, however, most private health insurance do not cover costs of such light illnesses that this paper analyses. Hence ignoring private health insurance does not induce much problem in this point.

A few remarks should be made concerning biases and errors. First, the survey covers only the Tokyo Metropolitan and Kansai areas, which are relatively urban areas. It would have been better to use data from all areas in Japan, but there are no other such data sets that contain such detailed information as does this survey. Second, the sample is confined to ages 20 to 69 because Individual Cards were distributed only to these people. It is true that hospital-related behaviors of the aged are of the public concern because of the rapid increase of the medical expenditure by the elderly. Since we focus on light illness here and the interaction between patients and physicians and the publicity of hospitals are outside of this paper, excluding the elderly from the sample would not be a major point of issue. Third, some problems about the timing when the people feel sick and when they fill in the Cards should not be overlooked. Since to write in or not depends on the decision of household members, some cases of very light illness may not be recorded if they need not go to hospital or take any medicine. Therefore it is possible that very light illnesses tended not to be logged. Finally, illness-related Behavior Record Cards do not contain daily logs. If the symptoms or behaviors did not change, these were recorded collectively. An observation might say that an individual attended a hospital every day for 3 months, but such observations are very few.

As noted above, our data has some caveats, but this might possibly be one of the best available sets of data in Japan, and contains rich information about economic aspects of health seeking behavior.

3 Econometric specification

This section explains econometric specification in this paper. Before proceeding, we overview the relationship between the copayment rate and medical expenditure.

The negative relationship between the copayment rate and medical expenditure is an old issue. Nagase [7], who was engaged in the development of the first public medical insurance system in Japan, found this relationship. The " Nagase effect" is an empirical rule that the medical expenditure, y, can be represented by the quadratic function of the copayment rate, x, as $y = 0.8x^2 - 1.6x + 1$ if there is no additional benefit. This formula says that if the copayment rate x is zero the medical expenditure, y, is one, while if x equals 1 y becomes 0.2.

The usual moral hazard or ex-post moral hazard can explain the negative relationship between copayment rate and medical expenditure. In the usual moral hazard context the logic is as follows: Because a reduction of the copayment rate reduces a monetary burden if people get sick, the incentive to prevent sickness decreases, and the probability of sickness rises. This makes medical expenditure increase, *ceteris paribus*. On the other hand, in the ex-post moral hazard context the behaviors after people get sick are emphasized. This assumes that the medical service is a normal good and that the demand for medical service is a decreasing function of its price, the copayment rate. As Ii and Ohkusa [8] point out, this assumption that the medical service is a normal good is open to question. Considering the asymmetry of information between patients and doctors, it may be natural that how much medical service patients consume is assumed to be decided by doctors. The two-part model says that the only decision that patients take is whether to go to hospital or not, and the physicians' induced demand model sheds light on the role of physicians to determine the demand for medical care service. These models can explain the negative relationship between the copayment rate and the number of visits, or between the copayment rate and the medical expenditure in an aggregate level.

Based on these theoretical models, many articles have been devoted to the study of measurements of price elasticity or the magnitude of the negative relationship between a copayment rate and the probability of a visit or medical expenditure. Some use linear regression or the Tobit model in which medical expenditure, number of visits or number of days in hospital is the dependent variable. Others use a discrete choice model in which to visit or not, or to take one of some alternatives is the dependent variable. A representative research of this type is found in RAND [1]. As many kinds of micro data have become available [9], most research has confirmed that "the demand for health care falls with increases in out-of-pocket costs", but that "the magnitude of the estimated response varies widely [10]. Reflecting this situation, highly developed statistical models are often utilized ([2], [11], [12]). As for Japan, some use aggregate data ([13], [14]), others use micro data ([15], [16], [17]) to find a statistically significant negative price elasticity

As Gilleski [5] describes, many studies, which consist of a Probit equation for the probability that people consult doctors or linear equations for medical expenditures, implicitly assume that people decide to consult a doctor or not before they get sick. This might not be realistic, and dynamic decision making should be incorporated. Gilleski [5] pays much attention to this aspect and develops a discrete choice stochastic dynamic programming problem. Her research is thorough, but here we employ a more traditional method. To solve a stochastic dynamic problem makes it possible to estimate structural parameters, but the number of estimated parameters is relatively small. The reason why we use a regression-like duration analysis here is to control for more characteristics and estimate price elasticity. For example, we are able to consider effects of symptoms which vary every day. Ii and Ohkusa ([15], [16]) use Probit equations but pay attention to dynamic decision making; incorporating as exogenous variables the quadratic function of the number of days from the day when one gets sick. They find that price elasticity varies between the different kinds of sickness. However they include samples taken after patients first go to hospitals.

This paper focuses on the decision to consult a doctor for the first time since a person felt sick(5). Because the timing of when they visit depends only on their decision, not on a doctor's decision, we can limit the discussion to the pure effect of ex-post moral hazard, excluding physician induced demand(6). We employ duration analysis for this purpose, in which the number of days from when people feel sick to when they visit a doctor is a dependent variable. The duration analysis focuses on the hazard rate, the instantaneous rate of change of states. This method is useful to analyze a situation day by day where people decide whether to consult a doctor as explanatory variables change. Here the change of states means that people decide to visit a doctor. That is, the initial state is a situation where they feel sick and stay home

(5)We focus on behavior of people, not on medical expenditure. Even if some people recover naturally without visiting doctors, delaying visiting does not necessarily reduce aggregate medical cost. This is because medical conditions may become worse if they do not go to medical institutions. To investigate such relationship is future research.

(6)Since the sample is consisted of those who feel sick, the effect of ex-ante moral hazard is not the point in question.

and the second state is a situation where they feel sick and visit a doctor. If an individual gets sick more than once during the sample period, multiple episodes of one individual are recorded in the data. In many cases people recover without visiting and we treat such cases as censored observations(7). In this paper we employ a sequential Probit model. This model is used to analyze recursive decision making. The specification in this paper is one of the more flexible specification proposed by [22] with coefficient constraints. Now we denote as $\lambda(k, \mathbf{x})$ a conditional probability that visiting hospitals on the k-th day since they feel sick conditional on exogenous variables, $\mathbf{x}$, and conditional on that they did not consult a doctor during the proceeding $k-1$ days. The conditional probability, $P(k|\mathbf{x})$, that they visit on the k-th day conditional on exogenous variables, $\mathbf{x}$, becomes

$$P(k|\mathbf{x}) = \lambda(k, \mathbf{x}) \prod_{j=1}^{k-1} [1 - \lambda(j, \mathbf{x})]. \tag{1}$$

We can formalize as a binary choice model the probability that people who did not visit a doctor during the proceeding $k-1$ days visit a doctor. We utilize the Probit model here and rewrite $\lambda(k, \mathbf{x})$ using the corresponding coefficient vector, β_k, and error term, ε_k, and get

$$\lambda(k, \mathbf{x}) = \lambda(\mathbf{x}_k' \beta_k + \varepsilon_k > 0). \tag{2}$$

If we further assume that the error term is sum of episode-specific random component, v, and standard error component, u_k, that the covariance matrix of the standard error component, $(u_1, u_2, \cdots, u_K)$, is the identity matrix, we only have to estimate the panel Probit model, as

(7) We can apply a competing risks model where the ‘risks’ are visiting and recovering. However, if we assume the conditional independence between the two risks, we can use a simple duration model where recovery observations are treated as censored ones.

if each day is one observation and each episode is one group. The model with this covariance matrix constraint is like those called an independent sequential Probit model (ISP). Although this constraint might not be so natural, to estimate a more flexible model (CSP: correlated sequential Probit model) is vary hard and we use this ISP in this paper.

Gilleskie and Mroz [22] represent $\lambda(k, \mathbf{x})$ as a fourth order polynomial function of the explanatory variables and allow the coefficients to vary according to each k(8). Their results of a Monte Carlo simulation show that this estimation method (approximate conditional density estimation) gives quite accurate estimates because of the less assumptions.

As our data is survival data, the number of observations falls as k increases. Therefore it is difficult to estimate a model where the coefficients vary especially for large k. We constrain the coefficients in $\lambda(k, \mathbf{x})$ to be same for all k ($\beta_k = \beta_j, \forall k, j$), and add dummy variables for each day to control time-series fixed effects. In our sequential Probit model, if the coefficient is positive, that means that the probability of visiting a doctor increases as the explanatory variable increases. To control unobserved heterogeneity we use random effect panel Probit model here.

We also use traditional duration model to check robustness. One is a piecewise-constant proportional hazard model and the other is an accelerated failure time model, whose functional form is log-logistic(9). We call the hazard function $h(t)$, survival function $S(t)$. The log likelihood

(8)As Gilleskie and Mroz [22] show, their method can be applied to continuous dependent variable. In fact the dependent variable in their paper is medical expenditure.

(9)See [18], [19], [20] for these models. For the Cox proportional hazard model, which is also often used in the survival analysis, see [21].

function can be written as

$$\begin{aligned} \ln L &= \sum_c \ln L_c + \sum_n \ln L_n \\ & \ln L_c = \ln S(t_i), \quad \ln L_n = \ln h(t_i) + \ln S(t_i) \end{aligned} \tag{3}$$

where c denotes censored observations, n represents non-censored observations. In this paper if the coefficient is positive, the hazard rate increases as the corresponding variable increases in the piecewise-constant proportional hazard model. This means that if the variable increases the period from when people feel sick to when they visit a doctor shortens. On the other hand, in the accelerated failure time model if the coefficient is positive, the survival function, $S(t)$, increases as the corresponding variable increases. This means that if the value of the variable goes up, the period gets longer.

These specifications, which are often used in duration analysis, require certain assumptions. The piecewise-constant proportional hazard model needs relatively less assumptions, but assumes a proportional hazard, which though it applies in many cases in medical science might not necessarily apply in this specific situation. The accelerated failure time model does not need a proportionality of a hazard rate, but it specifies the functional form.

We use as the time invariant explanatory variables copayment rate, female dummy, working dummy, educational variables, residence dummy (Kansai Area), household income, household financial assets, subjective health condition variables, age, people dummies who live together, and habit dummies (smoking and drinking). The time variant explanatory variables are dummies for fever, symptoms, alternative treatments (medicine, acupuncture and moxibustion treatment, counseling and folk remedy). Because subjective symptoms are accidental and people basically cannot control when they feel them, time invariant variables and dummies for fever and symptoms are exogenous for decision making. Since it may cause an endogeneity problem to use dummies for alternative treatments, we define these dummies so that it takes one if the individual had such therapies until the day before, and takes zero otherwise.

Logged behavior data is used in this paper, but we drop such observations of episodes that began before the survey period to avoid the left truncation problem(10). Moreover we do not use such episodes where the number of days to go to a hospital is more than 30.

4 Results

The episodic sample used here consists of 3910 observations. Sample statistics are shown in Table 2. The average copayment rate of public medical insurance is 27.6%, which means that many people face either a 20% or 30% copayment rate. To overview the sample Kaplan-Meier survival estimates (Figures 1 and 2) are used. Figure 1 shows that in about 50% of light-illness episodes people recovered without visiting a doctor. Figure 2 demonstrates the difference of Kaplan-Meier estimates according to copayment rate. The Kaplan-Meier curve of those whose copayment rate is zero is upward, while that of those whose copayment rate is 100% is downward. But the number of such people is relatively small. The Kaplan-Meier estimates of those who faced 10% lies on the lowest side among those of those who faced 10%, 20%, and 30% copayment rates, while the one of those who face 30% copayment rates lies on the most upper side. This means that given the days passing from when a person feels sick, the ratio of those who do

(10)The survey continued from May to November, but the Cards were collected at the end of August and November. Considering this structure of the survey, the episodes are treated as censored data that began at 1 May or 1 September or ended at the end of August and November.

not visit a doctor falls as the copayment rate rises. In other words, Figure 2 shows that those whose copayment rates are relatively low consult doctors sooner. It seems that this reflects ex-post moral hazard. We tested whether the curves are equal or not (Log-rank test, Wilcoxon test, Peto-Prentice test) to find if the differences are statistically significant (Table 3). However, Figure 2 and Table 3 do not control other characteristics.

The estimation results of sequential Probit are shown in Table 4. Specification (1) includes as explanatory variables copayment rate and time dummies. We add age variables in (2), add fever dummy, treatment dummies and time dummies in (3). Specification (4) includes all variables[(11)]. The estimated coefficients do not seem to vary dramatically.

First, the copayment rate does not have a statistically significant effect as a whole[(12)], and the estimated value of the coefficient is not so large. This means that the copayment rate does not change the length of the period from when people feel sick to when they visit a doctor. Considering that in the literature, the negative effect of a copayment rate on medical expenditure or the number of visits is reported, the results here might provide collateral evidence that interactions between patients and doctors cause a negative relationship. For example, doctors mighty offer more medical services for those whose copayment rate is relatively low. These results give some suggestions for public medical insurance reform. Recent reform has attempted to restrain medical expenditure by raising the copayment rate; however, since the results above show that the increase in the copayment rate might not affect the decision-making to start visiting a doctor, we cannot expect an effect of a raise in the copayment rate on the patient

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(11)Since the variables measuring risk aversion and time preferences do not show statistical significance, we drop these variables.

(12)The same result arises when we use dummies for each copayment rate.

decision itself. Taking into account the aggregate negative effect of the copayment rate on medical expenditure, the relationship between the copayment rate and the interaction between patients and doctors should be reexamined.

Alternative treatments (OTC medicine, acupuncture and moxibustion treatments, counseling and folk remedies) do affect the timing to visit a doctor. The effect of OTC medicine and folk remedies to delay visiting is detected as statistically significant; meaning that these treatments are substitute goods for visiting doctors. Taking into account natural healing, this result is consistent with the empirical evidence in [8], who show that people tend to take OTC medicine for an initial period of time but consult doctors when the sickness extends. The effect of counseling to hasten visiting is also negative, but it is not statistically significant.

Having a fever or feeling some symptoms have statistically significant effects to hasten going to see a doctor. Most symptoms bring forward the date of visiting, though not reported here.

The effects of other variables are as follows. The female dummy has a negative effect on the probability to visit a doctor. The working dummy shows an effect to hasten visiting, which suggests that working people give priority to curing sickness and getting back to working over paying costs(13) of visiting hospital. But this effect is relatively small. Subjective health conditions also affect behavior. People who believe their health condition is excellent are less likely to go to doctors, while those whose subjective health condition is poor are more likely to visit doctors. This may be because the expected benefit of visiting a hospital is relatively large for those who do not expect much natural healing, and is relatively small for those whose health conditions are good. In other words, those who have more health capital face less return from

(13)This cost means not only monetary costs. See [23].

investing in health capital [24]. The same logic also explains why those in their twenties do not tend to go to hospital while those in their sixties do. It cannot, however, be applied to smokers or to drinkers. Smoking or drinking habits delay visiting, which is not etected as statistically significant. This may mean that such people believe in natural healing, or that this is just because they do not like hospitals. Living together with the old or with children hastens consulting doctors; it is possible that such living together raises the time cost of going to hospital, but this result suggests that the effect of the increase in cost of taking care of the old or children overwhelm this time cost effect. The effects of household income and financial assets, which reflect households' economic power, are non-linear. It is difficult to interpret this, and we cannot find any well-marked relationships between the timing of visiting a hospital and a persons individual economic power(14).

The sequential Probit model estimated above constrains the coefficients such that they are all the same regardless of the day from when people feel sick ($\beta_k = \beta_j, \forall k, j$), but this constraint might not be so weak. We split the sample according to $k = 1$ or not and estimate by the same equation; Table 5 shows the results. It seems that the estimated coefficients are different between those of the first day and those of other days. Some coefficients which show statistical significance for overall sample become statistically insignificant for sample corresponding to the days after 1st day. On the other hand, the coefficients which are statistically significant for overall sample are also show statistical significance. These suggest that each factor has more effect on the behavior on the first day than on the following days. Namely, the behavior on later days is less affected by the characteristics of the individual or symptoms. One explanation for

(14)See [25] about the relationship between health and economic power in general.

this may be that days when people feel sick but do nothing to be cured are not recorded. Most of the results here are consistent with those noted above. The effect of the copayment rate is not statistically significant, and the magnitude is not so large. For example, a 10% point increase in the copayment rate just decreases the probability of visiting a doctor on the first day by 0.7%.

We also estimate the piecewise-constant proportional hazard models and the accelerated failure time model (Table 6). As noted above, in the piecewise-constant proportional hazard models, positive coefficients mean that the hazard rate increases and the period until the visit date shortens if the value of the corresponding variable increases. On the other hand, in the accelerated failure time model if the coefficient is positive $S(t)$ increases as the value of the corresponding variable becomes larger, which means that the period grows longer. The results are almost the same as those of the sequential Probit model. The coefficient of the copayment rate is relatively small and statistically insignificant, alternative treatments delay visiting doctors and so forth.

To check how our results are dependent to the definition of what constitutes a light illness, we also estimate the random probit model using sub-sample (Table 7). The episodes about cold and headache are used. Although the coefficients for cold and headache sub-sample are different than those using all episodes (Table 4), the coefficients of copayment rate are not statistically significant neither. Since our data sets may undersample male episodes as noted in Section 2, the random probit model using onle female episodes are estimated. The results are also shown in Table 7. The estimated coefficient of the copayment rate is not so far from that of Table 4 and this suggests that the sampling bias of our data set is not so serious.

To summarize the main points made in this section. First, it is difficult to say that the copayment rate has a strong effect on decision making whether to visit a doctor or not. Second, OTC medicine, acupuncture and moxibustion treatments, and folk remedies are substitute goods for seeing a doctor. Third, those who get more benefit from visiting a doctor, such as workers, those whose subjective health condition is poor, the aged and those who live together with the old or children, tend to go to hospital in the initial period of time of feeling ill.

5 Concluding remarks

This paper analyzes the behavior of those who feel sick but have not visited a doctor, putting emphasis on initial contact. It seems meaningful to examine the decisions made solely by such 'patients' when considering policies which try to control patients' behavior, since there is asymmetry of information between outpatients and doctors.

The following results are obtained: First, whether to visit a doctor or not is largely determined by the expected benefits. That is, not only those who have a fever or some symptoms, but workers, those whose subjective health condition is poor even at ordinary times, the aged and those who live together with the old or children tend to visit a doctor in the initial period of time of feeling ill. Second, it is difficult to say that the copayment rate has a strong effect on decision making whether to visit a doctor or not. Third, OTC medicine, acupuncture and moxibustion treatments, and folk remedies are substitute goods for visiting a doctor.

This paper pointed out the possibility that the monetary factor does not play an important role in decision making by patients. Considering that in the literature a negative effect of the copayment rate on medical expenditure or the number of visits is reported, the results here may provide collateral evidence that interactions between patients and doctors cause this negative relationship.

Based on the results presented in this paper, it is possible that increases in the copayment rate are not necessarily an effective measure to restructure public medical insurance finance. Therefore, introducing some non-monetary regulations or reforms of reimbursement system such as prospective payment system may be needed to better balance the budget of the National Health Insurance scheme. However, the analysis in this paper has some limits; one is that the data sets do not contain information about very aged people. Considering that the medical expenditure by the very aged people is growing rapidly, it is an important point. The increase in the copayment rate degrades the functionality of risk sharing of medical insurance, which might decrease the expected utility of people and lead to welfare loss. On the other hand, an increase in the copayment can affect preventive actions through a standard moral hazard mechanism. These are subject requiring future research.

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Table 1: Ratios of people who feel sick

	Male		Female	
Age	Our data	National Survey	Our data	National Survey
15-24	135.7	180.0	148.0	233.9
25-34	155.6	205.6	272.0	297.7
35-44	191.0	244.9	311.8	330.2
45-54	188.2	271.1	379.1	370.1
55-64	191.2	346.3	413.6	418.7
65-74	214.6	439.6	356.2	505.9
75-84	333.3	521.4	117.6	559.5

(Note) The values of our data represent ratios of who feels sick during the 1st week of June. "National Survey" in this table is National Livelihood Survey, which is conducted almost same period as our survey.

Table 2: Sample Statistics

	Average	Std. Err.	Max	Min
Copayment rate	0.276	0.111	1	0
Female dummy	0.714	0.452	1	0
Working dummy	0.557	0.497	1	0
Education				
Medical university	0.006	0.079	1	0
Non-medical university	0.254	0.435	1	0
Two-year university	0.182	0.386	1	0
Technical School	0.107	0.309	1	0
Other	0.004	0.060	1	0
Area dummy	0.388	0.487	1	0
Household income (yen)				
Less than 1 million	0.001	0.032	1	0
1 - 3 million	0.046	0.209	1	0
3 - 5 million	0.171	0.377	1	0
5 - 7 million	0.267	0.443	1	0
7 - 10 million	0.247	0.431	1	0
10 - 15 million	0.177	0.382	1	0
15 - 20 million	0.046	0.210	1	0
20 - 30 million	0.004	0.066	1	0
More than 30 million	0.004	0.062	1	0
Household financial assets (yen)				
Less than 1 million	0.125	0.331	1	0
1 - 3 million	0.168	0.374	1	0
3 - 5 million	0.111	0.314	1	0
5 - 7 million	0.072	0.259	1	0
7 - 10 million	0.105	0.307	1	0
10 - 15 million	0.096	0.294	1	0
15 - 20 million	0.064	0.245	1	0
20 - 30 million	0.082	0.274	1	0
More than 30 million	0.106	0.308	1	0
Subjective health condition				
Excellent	0.317	0.465	1	0
Good	0.529	0.499	1	0
Poor	0.147	0.354	1	0
Age				
20s	0.168	0.374	1	0
30s	0.215	0.411	1	0
40s	0.183	0.386	1	0
50s	0.256	0.437	1	0
60s	0.175	0.380	1	0
Living with				
The old	0.131	0.337	1	0
Children	0.308	0.462	1	0
Habit				
Drinking	0.292	0.455	1	0
Smoking	0.217	0.412	1	0

Figure 1: Kaplan-Meier Estimate (Total)

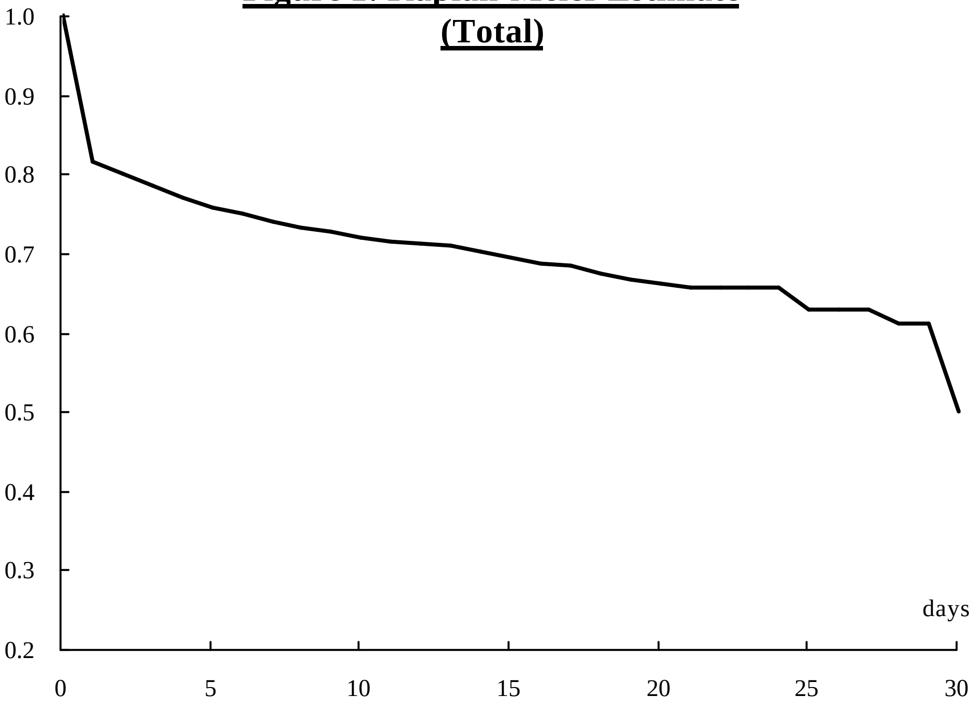

Figure 2: Kaplan-Meier Estimates

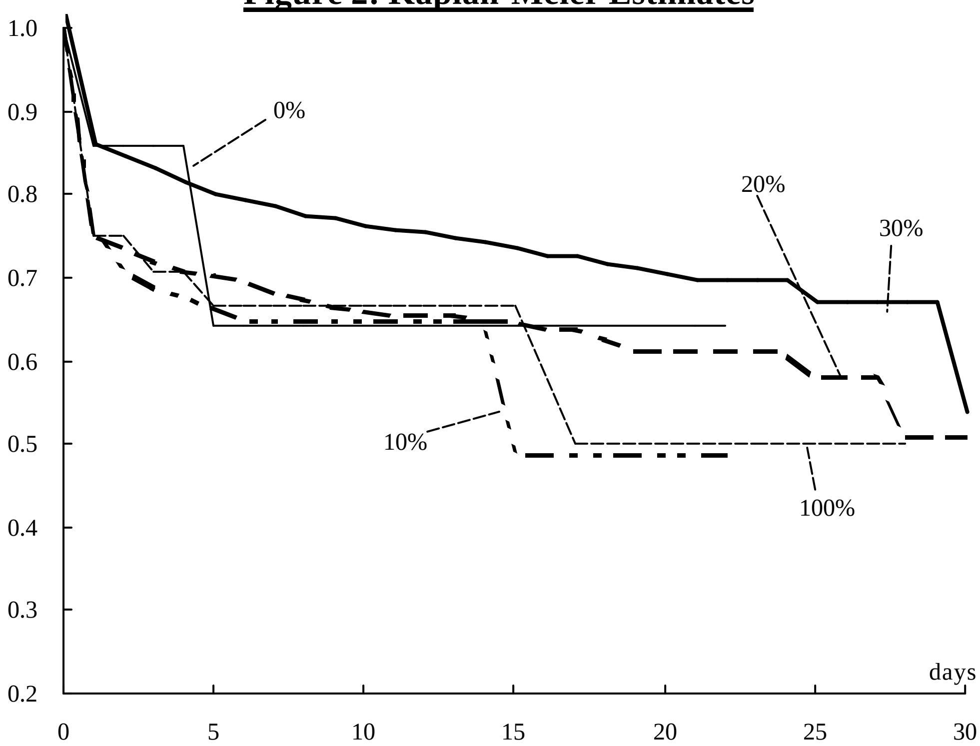

Table 3: Test of equality of survival function

	Logrank	Wilcoxon	Peto-Prentice
Statistics	41.53	49.02	42.65
p-value	0.000	0.000	0.000

Table 4: Estimation Results (random effect probit)

	(1)	(2)	(3)	(4)
	ME	ME	ME	ME
Copayment rate	-0.246	-0.150	-0.211	-0.188
Female dummy		-0.219 ***	-0.328 ***	-0.319 ***
Age				
20s		0.036	-0.173	-0.263 **
30s		0.187 ***	0.152	-0.021
40s		-0.021	-0.027	-0.167
60s		0.323 ***	0.609 ***	0.664 ***
Working dummy				0.151 *
Education				
Medical university				0.130
Non-medical university				0.049
Two-year university				0.029
Technical School				0.118
Other				0.388
Area dummy				0.058
Household income (yen)				
Less than 1 million				0.114
1 - 3 million				0.346 **
3 - 5 million				0.276 **
7 - 10 million				0.139
10 - 15 million				0.152
15 - 20 million				0.074
20 - 30 million				0.980 **
More than 30 million				0.493
Household financial assets (yen)				
Less than 1 million				-0.228
1 - 3 million				-0.042
3 - 5 million				-0.282 **
5 - 7 million				-0.129
10 - 15 million				0.045
15 - 20 million				-0.143
20 - 30 million				-0.466 ***
More than 30 million				-0.146
Subjective health condition				
Excellent				-0.104
Poor				0.559 ***
Living with				
The old				0.181 *
Children				0.262 **
Habit				
Drinking				-0.062
Smoking				-0.004
Fever dummy			1.171 ***	1.210 ***
Treatment dummies				
OTC medicine			-0.334 ***	-0.342 ***
Acupuncture and moxibustion treatment			-1.251 **	-1.338 ***
Counseling			-8.878	-7.903
Folk remedy			-0.454 **	-0.462 **
Symtoms dummy			Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	19955	19854	19854	19692
Log likelihood	-3052.2	-2968.0	-2707.8	-2656.2

(Note) The marginal effect (ME) represents the change of probability for discrete change from 0 to 1 if the variable is dummy variable. The reference group of education is `high school', that of household income is `5-7 million', that of household financial assets is ` 7-10 million', that of subjective health condition is `good', that of age is `50s'
*, **, *** represent statistically significant at 10, 5, 1 percent level respectively.

Table 5: Estimation Results (random effect probit)

	1st day		After 2nd day	
	ME		ME	
Copayment rate	-0.071		0.268	
Female dummy	-0.053	***	-0.084	
Age				
20s	-0.044	**	-0.029	
30s	-0.035		0.248	**
40s	-0.031		0.002	
60s	0.132	***	0.136	
Working dummy	0.014		0.147	**
Education				
Medical university	0.027		0.151	
Non-medical university	0.012		-0.016	
Two-year university	0.017		-0.107	
Technical School	0.035		-0.058	
Other	0.135		-7.393	
Area dummy	0.005		0.077	
Household income (yen)				
Less than 1 million	0.116		-7.523	
1 - 3 million	0.068	**	0.049	
3 - 5 million	0.047	**	0.129	
7 - 10 million	0.015		0.146	*
10 - 15 million	0.014		0.142	
15 - 20 million	0.016		-0.091	
20 - 30 million	0.247	**	-7.752	
More than 30 million	0.124		-7.347	
Household financial assets (yen)				
Less than 1 million	-0.035		-0.087	
1 - 3 million	-0.027		0.102	
3 - 5 million	-0.055	**	-0.028	
5 - 7 million	-0.030		0.047	
10 - 15 million	0.009		-0.019	
15 - 20 million	-0.032		0.097	
20 - 30 million	-0.076	***	0.006	
More than 30 million	-0.029		-0.011	
Subjective health condition				
Excellent	-0.027	*	0.077	
Poor	0.103	***	0.197	**
Living with				
The old	0.025		0.122	
Children	0.033	*	0.219	**
Habit				
Drinking	-0.020		0.092	
Smoking	0.022		-0.156	*
Fever dummy	0.250	***	0.709	***
Treatment dummies				
OTC medicine			-0.247	***
Acupuncture and moxibustion treatment			-0.744	**
Counseling			-6.936	
Folk remedy			-0.312	**
Symtoms dummies	Yes		Yes	
Time dummies	No		Yes	
Observations	3852		15890	
Log likelihood	-1607.3		-1005.2	

(Note) The marginal effect (ME) represents the change of probability for discrete change from 0 to 1 if the variable is dummy variable. The reference group of education is `high school', that of household income is `5-7 million', that of household financial assets is ` 7-10 million', that of subjective health condition is `good', that of age is `50s'.
*, **, *** represent statistically significant at 10, 5, 1 percent level respectively.

Table 6: Estimation Results (Duration model)

	Piecewise constant PH		Log-logistic	
	Coefficient		Coefficient	
Copayment rate	-0.151		-0.021	
Female dummy	-0.263	***	0.395	***
Age				
20s	-0.232		0.242	**
30s	-0.017		0.079	
40s	-0.156		0.105	
60s	0.528	***	-0.581	***
Working dummy	0.111		-0.154	**
Education				
Medical university	0.185		0.252	
Non-medical university	0.061		-0.003	
Two-year university	0.026		-0.030	
Technical School	0.077		-0.074	
Other	0.283		-0.020	
Area dummy	0.031		-0.052	
Household income (yen)				
Less than 1 million	0.141		0.127	
1 - 3 million	0.320	**	-0.289	**
3 - 5 million	0.208	**	-0.225	**
7 - 10 million	0.118		-0.176	**
10 - 15 million	0.087		-0.100	
15 - 20 million	0.012		-0.049	
20 - 30 million	0.730	**	-0.717	**
More than 30 million	0.381		-0.455	
Household financial assets (yen)				
Less than 1 million	-0.180		0.161	
1 - 3 million	-0.038		0.096	
3 - 5 million	-0.223		0.281	**
5 - 7 million	-0.152		0.169	
10 - 15 million	0.041		-0.053	
15 - 20 million	-0.095		0.047	
20 - 30 million	-0.361	**	0.498	***
More than 30 million	-0.144		0.144	
Subjective health condition				
Excellent	-0.073		0.068	
Poor	0.456	***	-0.426	***
Living with				
The old	0.169	*	-0.154	*
Children	0.262	***	-0.278	***
Habit				
Drinking	-0.039		0.124	*
Smoking	0.010		0.009	
Fever dummy	0.993	***	-1.028	***
Treatment dummies				
OTC medicine	-0.532	***	2.019	***
Acupuncture and moxibustion treatment	-2.353	**	3.291	***
Counseling	-12.449		10.084	
Folk remedy	-0.751	**	2.058	***
Symtoms dummies	Yes		Yes	
Time dummies	Yes		No	
Observations	19762		19762	
Log likelihood	-2484.8		-2630.9	

(Note) The reference group of education is `high school', that of household income is `5-7 million', that of household financial assets is ` 7-10 million', that of subjective health condition is `good', that of age is `50s'.

*, **, *** represent statistically significant at 10, 5, 1 percent level respectively.

Table 7: Estimation Results (random effect probit)

	Cold	Headache	Female
	Coef.	Coef.	Coef.
Copayment rate	0.472	-4.478	-0.024
Female dummy	-0.087	0.634	
Age			
20s	-0.341	-1.054	-0.161 *
30s	0.165	-1.068	-0.019
40s	-0.002	-1.779 *	-0.110
60s	1.113 ***	0.727	0.345 ***
Working dummy	0.193	-0.699	0.095 *
Education			
Medical university	0.006	-8.045	0.168
Non-medical university	0.173	0.445	-0.057
Two-year university	-0.314	0.376	-0.037
Technical School	-0.190	0.836	-0.033
Other	-0.701	-7.060	-7.226
Area dummy	-0.047	0.853 **	0.035
Household income (yen)			
Less than 1 million	0.849		-6.516
1 - 3 million	0.792 **	-0.055	0.196 *
3 - 5 million	0.225	0.586	0.225 ***
7 - 10 million	0.099	0.749	0.084
10 - 15 million	0.337	-1.365	0.141 *
15 - 20 million	0.090	-0.775	-0.065
20 - 30 million	0.327	-4.957	-0.445
More than 30 million	-0.695		1.315 **
Household financial assets (yen)			
Less than 1 million	-0.522 **	-0.036	-0.209 **
1 - 3 million	-0.088	-0.167	-0.038
3 - 5 million	-0.528 *	-0.353	-0.283 ***
5 - 7 million	-0.174	-0.362	-0.107
10 - 15 million	-0.375	-0.850	-0.105
15 - 20 million	-0.885 ***	-0.062	-0.074
20 - 30 million	-0.345	0.132	-0.330 ***
More than 30 million	-0.569	-1.258 *	-0.063
Subjective health condition			
Excellent	-0.193	0.232	-0.070
Poor	0.444 **	0.321	0.285 ***
Living with			
The old	0.155	0.442	0.154 **
Children	0.443 *	0.310	0.013
Habit			
Drinking	0.005	0.003	0.013
Smoking	0.039	0.139	0.011
Fever dummy	1.249 ***	2.863 ***	0.754 ***
Treatment dummies			
OTC medicine	-0.079	-1.104	-0.311 ***
Acupuncture and moxibustion treatment	-12.309	-7.866	-0.841 **
Counseling			-5.345
Folk remedy	-0.755 **	-6.838	-0.490 ***
Symtoms dummies	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Observations	4805	1531	14462
Log likelihood	-971.9	-54.2	-1747.6

(Note) The reference group of education is `high school', that of household income is `5-7 million', that of household financial assets is ` 7-10 million', that of subjective health condition is `good', that of age is `50s'.

*, **, *** represent statistically significant at 10, 5, 1 percent level respectively.