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Measuring income equity in the demand for healthcare with finite mixture models

The paper exploits panel data finite mixture (latent class) models to measure consumer equity in healthcare access and utilization. The finite mixture approach accounts for unobservable consumer heterogeneity, while generalized linear models address a retransformation problem of logged dependent variable. Using the data of the Japan Household Panel Survey (2009–2014), we discover that consumers separate into latent classes in the binary choice models for healthcare use and generalized linear models for outpatient/inpatient healthcare expenditure. The results reveal that healthcare access in Japan is pro-poor for the most sick consumers, while utilization of outpatient care is equitable with respect to disposable income.

Keywords: healthcare demand; equity; generalized linear models; latent class; finite mixture.
JEL classifications: I10; I18; G22; R22.

1. Introduction

Guaranteeing equity for the poor is a major challenge for healthcare systems in developed countries. Overall, equity is an ethical issue related to the judgments about healthcare accessibility[2]. At the same time, an economic concept of horizontal equity deals with «an equal treatment for equal need» (Wagstaff et al., 1991a; Culyer, Wagstaff, 1993) and «means that persons in equal need of medical care should receive the same treatment, irrespective of whether they happen to be poor or rich» (Wagstaff et al., 1991b). In practical terms, there is a general agreement about striving for «minimal variation of [healthcare] use with income» (Newhouse et al., 1981) and ensuring equity for the poor (Wagstaff, van Doorslaer, 2000b; Cutler, 2002).

According to theoretical predictions, a well-designed social health insurance system may provide an equitable redistribution of medical care between the rich and the poor (Zweifel, Breyer, 2006). However, the actual performance of social health insurance systems with respect to guaranteeing equity for the poor is an ultimately empirical question (Hurley, 2000; van Doorslaer et al., 2004; Rannan-Eliya, Somanathan, 2006; Wagstaff, 2010). The most prevalent method for analyzing income equity exploits regression analysis and estimates coefficients for income group variables in the equation for healthcare utilization, with equality of the coefficients interpreted as zero inequity (Wagstaff, van Doorslaer, 2000a; Jones, Wildman, 2008). Indeed, the non-rejection of the null hypothesis of equality of coefficients for income groups provides a

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2 As is defined in *The Dictionary of Health Economics*, equity «relates in general to ethical judgments about the fairness of income and wealth distributions, cost and benefit distributions, accessibility of health services, exposure to health-threatening hazards» (Culyer, 2005).

sufficient condition for zero inequity in terms of an alternative approach, which measures concentration indices (Wagstaff, van Doorslaer, 1991b; Wagstaff, van Doorslaer, 2000a; Wagstaff, van Doorslaer, 2000b). Such analyses regard consumer's health condition as the major covariate that controls for the actual *need* of healthcare[3]. Yet, the variables available in most microdata surveys (e.g., self-assessed health) may mail fail to fully capture the health status of the respondent. Therefore, incorporating unobservable heterogeneity, related to the decisions about healthcare use and the amount of healthcare purchased, is essential for raising the precision of the estimations of healthcare demand.

The purpose of this paper is to account for unobservable consumer heterogeneity in measuring income equity in healthcare access and utilization. The novelty of the paper is twofold. Firstly, we examine inpatient and outpatient healthcare access, and analyze expenditure within health insurance, exploiting the longitudinal data of the Japan Household Panel Survey. The unique feature of the survey is the fact that it distinguishes between non-users of healthcare, the users of inpatient and outpatient care, and provides a wide range of consumer characteristics, such as health status, index of psychological distress and life-style variables. Secondly, we measure income inequity by exploiting the generalized finite mixture models for healthcare use in the longitudinal context. The approach encompasses unobservable consumer characteristics with the finite mixture models (Deb, Trivedi, 1997), as well as exploits generalized linear models for solve the retransformation problem of logged dependent variable (Nelder, Weddernburn, 1972; McCullagh, Nelder, 1989). The paper uses the Greene's (2007) methodology for estimating panel data generalized linear models with latent classes.

It may be noted that the applicability of the finite mixture models for analyzing healthcare demand is well established (Cameron, Trivedi, 2013; Jones et al., 2013). However, the use of generalized finite mixture models for measuring healthcare expenditure is generally limited to experimental literature or cross-sectional estimates (Deb, Burgess, 2003; Baldi et al., 2013; Jones et al., 2013, Besstremyannaya, 2012). To the best of our knowledge, the panel data generalized finite mixture models applied in our earlier analysis of the price effects for healthcare demand (Besstremyannaya, 2015) might be the only related paper in the longitudinal setting.

The results of our estimations indicate that consumers separate into two latent classes in the binary choice models for use of any care or inpatient care, as well as in the loglinear and generalized linear models for outpatient and inpatient healthcare expenditure. The classes may be naturally interpreted as most frequent and most seek consumers («high users»), infrequent and most healthy consumers («low users»), and consumers with median use and median health status («median users»).

The coefficients for low income quintile are positively significant in the binary choice models for healthcare access by the most sick and most healthy consumers. The coefficients are generally insignificant in the models for healthcare expenditure. The results of the estimations reveal that healthcare access in Japan is largely pro-poor, especially for most sick consumers. At the same time, healthcare utilization proxied by outpatient expenditure is fully equitable. However, certain inequity may be found in health insurance premiums and the prevalence of catastrophic healthcare coverage by income groups.

Along with the methodological contribution in terms of the applied econometric approach, the results in the paper add to the discussion about equity in the Japanese social health insur-

[3] Indeed, the healthy and the sick have different income elasticity of healthcare expenditure (Nyman, 2006).

ance system. Indeed, the earlier findings are extremely mixed: income effect is insignificant according to the results of some research (Senoo, 1985; Sawano, 2001; Ii, Ohkusa, 2002; Kawai, 2007; Tokuda et al., 2009; Kawai, 2010), while other literature finds a positive and significant income effect (Bessho, Ohkusa, 2006; Babazono et al., 2008; Ishii, 2011).

The remainder of the paper is structured as follows. Section 2 outlines various aspects of equity in Japanese social health insurance system. Section 3 sets up the empirical models for measuring the demand for healthcare. Section 4 describes the data of the Japan Household Panel Survey. The findings of the empirical estimations with panel data binary choice models, loglinear and generalized linear models with latent classes, along with the analysis of the goodness-of-fit are summarized in Section 5. Section 6 discusses equity in Japanese social health insurance system. A review of the studies on income effect for healthcare demand in Japan is presented in the Appendix.

2. Background on health insurance in Japan

Mandatory and universal social health insurance system in Japan was established in 1961 and celebrated its semicentennial anniversary[4]. The enrolment in one of the non-intersecting health insurance plans is obligatory and depends on enrollee's age and status at the labor market. The major health insurance plans include: 1) national health insurance, which is municipality-managed insurance for self-employed, retirees, and their dependents; 2) government-managed insurance for small firms' employees and their dependents, and 3) company-managed insurance associations formed by firms with over 700 employees for employees and their dependents. The year 2008 saw a creation of a special plan for the elderly (aged 70 and above).

Japanese social health insurance system is equitable in terms of the choice of healthcare facilities, the list of available healthcare services, the size of nominal coinsurance rate, and the prices charged by providers. The users of any health insurance plan can seek care at any healthcare institution, regardless of its location or type (e.g., private/public, hospital, clinic or ambulatory division of hospital). There are no gatekeepers, and an amendment to Health Insurance Law, which introduced minor payments for turning to a large facility without referral, was passed only in 1996[5].

While the amount of insurance premiums is determined by each of the health insurance plans, the types of medical services and drugs to be offered within social health insurance and their costs (i.e., provider prices) are set by the Ministry of Health, Labor, and Welfare (MHLW) in a biennially revised unifying fee schedule[6]. The schedule ensures equal prices for similar types of healthcare institutions.

The size of nominal coinsurance rate for non-elderly adult population varied in the 0–50% interval, but became a flat value of 30% for enrollees of all health insurance plans since 2003.

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[4] See the series *Japan: Universal Healthcare at 50 Years* in *Lancet*'s issue of September 17, 2011.

[5] A payment for the first visit to a large hospital (with over 200 beds) without referral would normally vary from 1570 yen to 5250 yen.

[6] With the exception of obstetrics, preventive care, cosmetology and a number of additional types of treatment, balance billing, i.e. «charging the patient over and above the reimbursement from health insurance» (Ikegami, Campbell, 2004), is prohibited in Japan (Ikegami, 2006).

Although consumers pay out-of-pocket for the incurred healthcare costs according to the nominal coinsurance rate, they are compensated in case of high medical expenditure. The system of high-cost medical benefits (also called catastrophic coverage) aims at enhancing income equity in healthcare access and utilization. Consumers get refunds if their healthcare expenditure reaches a certain cap (Table 1). Accordingly, the nominal coinsurance rate for expenditure above the cap may become as low as 1%. Moreover, consumers with the lowest income face the cap of 35400 yen a month, receiving the rest of the health insurance care for free. Owing to the system of high-cost medical benefits, the values of the actual share of out-of-pocket expenditure incurred by an enrollee (so called effective coinsurance rate) are almost twice lower than the nominal coinsurance rate (Ikegami, Campbell, 1999; Imai, 2002; Ikegami, Campbell, 2004; Ikegami, 2005).

Table 1. High-cost medical benefits for adult Japanese consumers

Income category	Caps on monthly out-of-pocket health insurance expenditure
High income (above 530 000 yen a month)	150 000 yen + (healthcare expenditure – 500 000 yen) ×1% [83 400 yen]
General category	80 100 yen + (healthcare expenditure – 267 000 yen) ×1% [44 400 yen]
Low income (i.e. those exempt from residence taxes)	35 400 yen [24 600 yen]

Source: (Ministry of Health…, 2011, p. 17).

Notes. The table shows the caps for one to three high-cost medical benefits per 12 months. Figures in brackets correspond to the fourth within 12 months. All monetary values in the table are reported according to the reform of October 2008. The thresholds for residence tax exemptions vary in each municipality.

The lowest income category are consumers exempt from paying resident taxes, and the size of income to qualify for the exemption is set at the level of each municipality. Therefore, income thresholds may differ up to two times across the affluent municipalities in the Tokyo metropolitan area and the unprosperous small towns in the North or South of the country. Overall, the safety net and the income thresholds are likely to depend on the fiscal situation in the municipality (Ikegami et al., 2011).

The studies of poverty and deprivation in Japan have mixed results about income effect on the amount of healthcare expenditure (See review in Appendix). It should be noted that income effect is rarely analyzed with respect to income group. Even when income groups are introduced (e. g., Bessho, Ohkusa, 2006; Tokuda et al., 2009), threshold values for low and middle-income groups are arbitrary chosen.

3. Empirical models

Following Gravelle et al. (2006), we assume healthcare utilization by individual i may be expressed as $y_{it} = f(x_{1i}, x_{2i}, s_i)$, where x_{1i} denotes *need* variables (covariates that should have significant estimated coefficients, such as state of health), x_{2i} stands for *non-need* variables (covariates that should *not* have an effect on healthcare utilization, for instance income), and s_i indicates supply variables.

Below we outline econometric models for healthcare access, interpreted as the binary choice of going to clinic/hospital, and for healthcare utilization, which is proxied by the amount of healthcare expenditure. A vector of need variable includes self-assessed health, body mass index, index of psychological distress, and other consumer characteristics, as explained in the Data section.

As for the non-need variables, we believe that employing income percentiles (Ishii, 2011; OECD, 2009) is the most applicable approach for analyzing income inequity in a sample, which encompasses many unknown municipalities with different levels of poverty lines. Note that quintile analysis is commonly used in the studies of horizontal equity in the OECD countries (van Doorslaer et al., 2004). Accordingly, to address income equity in healthcare access and incurred healthcare costs (Culyer, Wagstaff, 1993), our empirical analysis focuses on the examination of the estimated coefficients for income quintiles.

Due to unavailability of municipality names in our data, we limit the vector s_i to the dichotomous variables for designated cities and other cities. The approach accounts for better healthcare supply in Japanese cities relative to rural areas.

The estimations in this paper exploit the Duan et al.'s (1983) multi-part model, which considers individuals who make independent decisions about purchasing healthcare and the amount purchased. The approach is particularly applicable to Japanese healthcare market with the strong degree of trust between physician and patient, so patients would follow physician's recommendations about the treatment (Muramatsu, Liang, 1996)[7].

3.1. Multi-part model

The model distinguishes between non-users of healthcare, users of inpatient and outpatient care. The model incorporates binary choice equations and is estimated using maximum likelihood method, with each equation of the model estimated separately owing to an additive log-likelihood function (Duan et al., 1983). Let

$$\Pr(y_i > 0) = F(y_i, x_i'\beta_1)\,, \tag{1}$$

$$\Pr(inpatient_i > 0 \mid y_i > 0) = F(inpatient_i, x_i'\beta_2)\,, \tag{2}$$

$$\log(y_i \mid y_i > 0,\, inpatient_i = 0) = x_i'\beta_3 + \varepsilon_i\,, \tag{3}$$

$$\log(y_i \mid inpatient_i > 0) = x_i'\beta_4 + \nu_i\,, \tag{4}$$

$$\mathrm{E}\varepsilon_i = \mathrm{E}\nu_i = \mathrm{E}(x_i'\varepsilon_i) = \mathrm{E}(x_i'\nu_i) = 0\,, \tag{5}$$

where i is the index for observation, y_i denotes healthcare expenditure, $inpatient_i$ indicates healthcare expenditure during hospitalization, and x_i are covariates. The dependent variables y_i in (3) and (4) are taken in logs due to the skewness of health expenditure data and zero mass problem (i.e., the fact that healthcare expenditure is truncated at zero).

[7] A sample selection (Heckman, 1979) model, where the two processes are not independent, does not fit our data.

3.2. Finite mixture models

The finite mixture approach (Deb, Trivedi, 1997; Deb, Holmes, 2000) divides observations into unobservable classes (components) to account for immeasurable consumer characteristics, related to healthcare demand but not captured by self-assessed health and other control variables. Formally, the dependent variable y_{it} is observed over time periods $t = 1,...,T$. The observations come from a mixture of J components (classes or subpopulations) in unknown proportions $\pi_j > 0,\ j = 1,...,J$ which are called prior probabilities of class membership and sum up to unity. The unconditional probability density of y_{it} is the sum of conditional probability densities, so $f(y_i \mid \pi,\theta) = \sum_{j=1}^{J} \pi_j f_j(y_i \mid \theta_j)$, where $f_j(y_i \mid \theta_j)$ is the component density and θ_j are the values of parameters, which determine separation into subpopulations. The model assumes the presence of independent repeated measurements of the dependent variable over time. Therefore, the component density is obtained as the product of the densities in each period: $f_j(y_i \mid \theta) = \sum_{j=1}^{J} \pi_j \cdot \prod_{t=1}^{T} f_j(y_{it} \mid \theta_j)$. In case of unbalanced panels, the densities in the periods with absence of data are replaced by unity (Wedel, DeSarbo, 2002; Greene, 2007). The intuitive interpretation of the setup implies that the observation remains in the same latent class within each moment of time.

The classes may be interpreted as frequent and infrequent users of healthcare. Accordingly, the approach implies an implicit ordering of the classes and prior class probabilities, which can be accomplished within the rearrangement after the estimation (Cameron, Trivedi, 2013). For instance, in case of a two-class model the ordering, which looks like $\mathrm{E}y_1 > \mathrm{E}y_2$, indicates that index 1 stands for consumers with higher values of the dependent variable y (class 1) and index 2 denotes consumers with lower values of the dependent variable y (class 2).

Prior class probabilities are commonly estimated in the multinomial logit form. Namely,

$$\pi_j = \frac{\exp\theta_j}{\sum_{j=1}^{J}\exp\theta_j}, \quad \theta_J = 0. \tag{6}$$

The general formulation of the model allows for π_j to be functions of covariates. Accordingly, we consider π_{ij} in equation (7), although the subscript i is redundant in our case, as no covariates except for constant are introduced in (6).

Posterior joint probability $\Pr(i \in j)$ of belonging to component j is computed using the Bayes theorem:

$$\Pr(i \in j) = \frac{\pi_{ij} \cdot \prod_{t=1}^{T} f(y_{it} \mid x_{it}, \theta_j)}{\sum_{j=1}^{J} \pi_{ij} \cdot \prod_{t=1}^{T} f(y_{it} \mid x_{it}, \theta_j)}, \tag{7}$$

where π_j is a prior class probability from (6) and $f(y_{it} \mid x_{it}, \theta_j)$ are probability densities for observation *i* conditional on class *j* in a period *t*. Choosing the maximum value of $\Pr(i \in j)$ across all *j*, the most probable latent class for observation i is determined[8].

3.2.1. Binary choice model

The binary choice models (1) or (2) are extended to finite mixture models as follows (see Greene (2007) for details):

$$\Pr(z_{it} = 1 \mid x_{it}, u_i, j) = \Phi(x'_{it}\beta_j + \delta_j), \tag{8}$$

$$y_{it} \mid u_i = x'_{it}\beta_j + \varepsilon_{it} + u_i, \tag{9}$$

$$\varepsilon_{it} \sim N(0,1), \quad u_i \sim N(0, \sigma_u^2), \; u_i \text{ is uncorrelated with } x_{it}, \tag{10}$$

where *i* is the index for consumers; *t* is the index for year; *j* is the index for component (only constant term varies across classes in the implementation in LIMDEP); z_{it} is a binary variable which equals unity if healthcare expenditure is positive and zero otherwise; y_{it} is healthcare expenditure; x_{it} are covariates related to the demand for healthcare; β_j are coefficients for the *j*-th class, π_j and $\Pr(i \in j)$ are estimated according to (6) and (7).

3.2.2. Loglinear model

For observations with $y_{it} > 0$, let

$$\log(y_{it}) = x'_{it}\gamma_j + \xi_{it} + \nu_i, \tag{11}$$

$$\mathrm{E}\nu_i = \mathrm{E}\xi_{it} = 0, \; \xi_{it} \text{ and } x_{it} \text{ are non-correlated}, \; \nu_i \text{ and } x_{it} \text{ are non-correlated}, \tag{12}$$

where y_{it} is healthcare expenditure; x_{it} are covariates, j is the index for component, γ_j are coefficients for *j*-th component, π_j and $\Pr(i \in j)$ estimated according to (6) and (7).

3.2.3. Generalized linear models

Owing to the retransformation problem in the models with logged dependent variable (Duan, 1983; Manning, 1998; Mullahy, 1998), estimating linear model (11)–(12) can yield unbiased predictions only when error terms are normal or homoscedastic. A solution to the retransformation problem in case of non-normal and heteroscedastic errors is the use of generalized linear models (Nelder, Wedderburn, 1972; McCullagh, Nelder, 1989; Mullahy, 1998; Blough et al., 1999). Although there are other possible solutions[9], the advantages of generalized linear models

[8] Note that estimating the fitted values of the dependent variable by assigning each observation to the most probable component may not be a most accurate approach. Indeed, the classes are «latent» (i.e. not exactly determined) and, thus, the assignment involves an approximation. An alternative approach takes a weighted average of the fitted values of each observation in all latent classes (Greene, 2005).

[9] There are several alternative ways to deal with heteroscedasticity. Among them are Manning's (1998) method, which is particularly easy to implement if heteroscedasticity is present across mutually exclusive groups; semi-para-

are improved precision and robustness of the estimate of the conditional mean (Manning, Mullahy, 2001). Generalized linear model specifies the mean and variance functions for the dependent variable by setting a family of distributions $g(\cdot)$, as well as the link function, which is logarithmic in our case. This paper uses LIMDEP 9.0 to analyze the panel data finite mixture models for nonnegative dependent variables with several distribution families. Let

$$\log\left(\mathrm{E}(y_{it} \mid x_{it}, \theta_j)\right) = x_{it}'\beta \text{ and } (y \mid x_{it}, \theta_j) \sim g(y_{it}, x_{it}, \theta_j), \tag{13}$$

where $g(\cdot)$ is a family of distribution, x_{it} are covariates, β are coefficients and θ_j are ancillary parameters for the j-th component (Greene, 2007). The ancillary parameters include shape parameters in the distribution family and prior class probabilities.

3.2.4. Model comparison

The comparison of the goodness-of-fit between loglinear and generalized linear models is conducted with the analysis of residuals: raw bias, mean squared error, and mean absolute prediction error. Additionally, Greene (2007) proposes the following statistics to test between $\mathbf{H_0}$: «a latent class (unrestricted) model» and $\mathbf{H_a}$: «a model without latent classes (restricted model)»:

$$L = 2(\log L_u - \log L_r) \sim \chi^2\left((J-1)(k+1)\right), \tag{14}$$

where $\log L_u$ is loglikelihood of the unrestricted model, $\log L_r$ is loglikelihood of the restricted model, J is the number of latent classes, and k is the number of estimated parameters.

Although the statistics L corresponds to the general logics of likelihood ratio test for nested models, Greene (2007, E17.10.5) argues that the use of conventional information criteria may be more preferable in the applied analysis. Therefore, to choose between the models with and without latent classes (or with different number of classes), we use both Greene's (2007) test as specified in (14), and follow Cameron, Trivedi (2013) to examine the values of log likelihood function per se, information criteria (e.g. AIC) and goodness-of-fit in terms of the residual analysis.

4. Data

The paper uses the six most recent waves of data from Japan Household Panel Survey (2009–2014). The survey was established in 2009 as a nationally representative annual survey of adults. Respondents aged above 20 answer a wide range of questions on their labor activity, income and expenditure, socio-demographic characteristics, anthropometry, health, and health-related lifestyles in the previous year. There are a number of important features of this longitudinal survey for the purposes of the analysis of healthcare demand. First, healthcare access/utilization is reported at the individual level[10]. Second, it is divided into healthcare in outpatient and inpa-

metric approaches and extensions of generalized linear models (Basu, Manning, 2009). Recent reviews of the applied literature with generalized linear models and other methods for modeling healthcare expenditure may be found in Mihaylova et al. (2011), Mullahy (2009), Basu and Mullahy (2009), Buntin and Zaslavsky (2004).

[10] While in Japanese Panel Survey of Consumers and Keio Household Panel Survey healthcare expenditure is reported at the household level.

tient facilities. Finally, healthcare expenditure distinguishes the expenditure covered and non-covered by health insurance.

The binary choice in our analysis is modeled through dichotomous variables «healthcare» for using any healthcare facility (corresponds to equation (1)), and «inpatient care» for seeking care in an inpatient facility given consumer used some healthcare facility (3). The intensity variable «expenditure» is out-of-pocket payments for healthcare covered by health insurance (equations (3) and (4)).

We construct dichotomous variables «group1» through «group5» for quintiles of the annual disposable (after-tax) household income, with the upper quintile — «group5» — treated as a reference category. Five interaction terms (income group×log of annual disposable income) are added to the list of regressors to estimate income elasticity in each quintile. Individual characteristics are age, gender, binary variables for graduate education (available as of 2009 survey), and employment. Health status is taken into account with a binary variable for low health condition, Ben-Sira's (1982) psychological distress index (PDI), and body mass index (BMI). Binary variables for drinking and smoking reflect risky behavior which may impact health. The binary variables for designated city and other cities capture healthcare supply which is generally better in Japanese urban areas (rural areas, i.e., towns and villages become a reference category)[11]. We add a dummy for National Health Insurance, since there are additional high-cost medical benefits for the poor in this health insurance plan.

The analysis uses a subsample of non-elderly consumers (aged below 70), since Japanese elderly have lower nominal coinsurance rates[12] and special thresholds for high-cost medical benefits (Table 2).

Table 2. Descriptive statistics for the unbalanced panel in 2009–2014

Variable	Definition	Mean	St. Dev.	Min	Max
healthcare	1 if out-of-pocket expenditure for health care covered by health insurance is positive in the previous year; 0 otherwise	0.61	0.49	0	1
inpatient care	1 if used inpatient care and out-of-pocket expenditure for healthcare covered by health insurance is positive in the previous year; 0 otherwise	0.05	0.22	0	1
expenditure	Out-of-pocket expenditure for healthcare covered by health insurance the previous year, thousand yen	42.10	107.60	0	2400
income	Disposable household income in the previous year, thousand yen	5191.38	3495.64	20	120000
age	Years of age as of January 31 of the survey year	48.0	13.30	19	69
gender	1 if female; 0 if male	0.48	0.50	0	1
education	1 if completed junior college, college or university as of January 2009	0.44	0.49	0	1
work	1 if was employed last month	0.77	0.42	0	1
designated	1 if lives in a designated city, 0 otherwise	0.27	0.44	0	1
city	1 if live in a non-designated city, 0 otherwise	0.62	0.49	0	1

[11] The migration across the two types of cities and towns/villages is minor over the waves of 2010–2014, and about 9% of nonelderly respondents reside in rural areas. However, no rural residence is reported in 2009 and the city residence is often inconsistent with the data for later years. So we replace the residence in 2009 with the data for 2010, where available.

[12] Since 2007 nominal coinsurance rate is 10% for aged above 75 and 20% for aged 70–74.

End of the Table 2

Variable	Definition	Mean	St. Dev.	Min	Max
lowhcond	1 if self-assessed health condition is reported as «not very healthy» or «not at all healthy»; 0 if self-assessed health condition is reported as «very healthy», «rather healthy» or «average health»	0.10	0.31	0	1
PDI	Physiological distress index, calculated as the sum of responses to 8 questions on the recent presence of the below conditions (each response is on a four-point scale, where «one» refers to «often», «two» means «sometimes», «three» implies «almost never», and «four» stands for «never»): *headache or dizziness; palpitation or shortness of breath; sensitive stomach and intestines; backache or shoulder pain; get tired easily; catch a cold easily;* *feel reluctant to meet people; dissatisfied with present life*; *anxiety over future*	25.40	5.38	9	36
BMI	Body mass index = weight/height^2 (kg/m^2)	22.70	3.43	13.84	64.92
smoking	1 if currently smokes; 0 otherwise	0.26	0.44	0	1
drinking	1 if drinks moderately or heavily; 0 otherwise	0.64	0.48	0	1
NHI	1 if National Health Insurance; 0 other health insurance plan	0.29	0.46	0	1

Note. The total number of observations is 12 272 with 3174 individuals in the unbalanced panel.

5. Empirical results

5.1 Binary choice model for healthcare use

According to the results of the test for normality of errors (Greene, 2007, E18.60), we use probit model for binary choice equations of the four-part model (equations (1) and (2)). For each equation we estimate a model without latent classes and two to four latent classes, as the models with five classes fail to converge. The prior probabilities for class membership are significant in the models with two to four classes, and Greene's (2007) likelihood ratio test rejects the null hypothesis of the model without latent classes. We use the values of log likelihood function and AIC to choose between the models with different number of classes. The values of these statistics, which are presented in Table 3, indicate that the model with three classes is most preferable for (1) and (2): there are evident gains in the values of log likelihood function and AIC, when the number of classes is increased from two to three, while the gains under a more granular division into four classes are minor. Additionally, the division of consumers into four classes maybe unreasonable given our sample size of only 3174 individuals, while three classes are naturally interpreted as «high», «median» and «low» users.

Accordingly, for each equation we estimate probit model with three classes. Marginal effects for each covariate in case of any care or only inpatient care are given in Tables 4 and 5, respectively. The results indicate that the coefficients for marginal effects for the lowest income quintile are positively significant at the classes of high users and low users of any health care (Table 4). At the same time, the marginal effect of the low income group for median users is negative. The facts implies the Japanese health system is pro-poor in terms of access to outpatient and inpatient care for consumers with the highest and the lowest demand for healthcare.

Table 3. Comparison of the panel data probit finite mixture models for healthcare use

	Fmm-1	Fmm-2	Fmm-3	Fmm-4
	Model for any healthcare			
log L	–6819.5	–6854.7	**–6791.7**	–6758.5
AIC	13685.0	13799.5	**13719.4**	13699.0
	Model for inpatient care			
log L	–2315.6	–2299.7	**–2271.7**	–2249.2
AIC	4677.3	4689.4	**4679.3**	4680.5

Notes. Fmm-1 stands for the models without latent classes. Fmm-2, Fmm-3 and Fmm-4 indicate models with two, three and four latent classes, respectively. AIC $= -\log L + 2k$, where k is the number of parameters. Statistics for the preferred models are in bold.

Table 4. Marginal effects in the binary choice equation for any healthcare: panel data finite mixture probit model

	Latent class 1 (high users)		Latent class 2 (low users)		Latent class 3 (median users)	
constant	0.315	(0.539)	–1.571	(1.010)	–0.526	(0.323)
age	0.003	(0.021)	0.002	(0.067)	0.007	(0.041)
PDI	–0.003	(0.024)	–0.002	(0.068)	–0.009	(0.049)
BMI	0.002	(0.033)	–0.001	(0.093)	0.004	(0.074)
group1 × log(income)	–0.046	(0.036)	–0.106	(0.076)	0.093	(0.056)
group2 × log(income)	0.020	(0.167)	0.056	(0.448)	0.067	(0.318)
group3 × log(income)	0.015	(0.249)	0.358	(0.705)	–0.182	(0.535)
group4 × log(income)	–0.073	(0.218)	–0.218	(0.451)	0.012	(0.395)
group5 × log(income)	0.008	(0.006)	0.022	(0.025)	0.006	(0.012)
gender	–0.003	(0.011)	–0.032	(0.033)	0.067***	(0.025)
education	0.029***	(0.01)	0.065**	(0.029)	0.112***	(0.022)
group1	0.168*	(0.086)	0.961***	(0.086)	–0.593***	(0.172)
group2	–0.173	(1.65)	–0.194	(0.843)	–0.503	(1.012)
group3	–0.119	(3.272)	–0.842	(0.815)	0.687	(0.488)
group4	0.402	(0.791)	0.999***	(0.006)	–0.061	(1.94)
lowhcond	0.036***	(0.015)	0.120*	(0.064)	0.162***	(0.033)
smoking	–0.026*	(0.013)	–0.053	(0.029)	–0.139***	(0.025)
drinking	–0.023**	(0.01)	–0.036	(0.032)	0.054***	(0.023)
NHI	–0.013	(0.012)	0.011***	(0.029)	0.000	(0.024)
work	–0.011	(0.015)	–0.095**	(0.038)	–0.049*	(0.026)
designated	–0.009	(0.018)	–0.077	(0.037)	0.010	(0.039)
city	0.009	(0.016)	–0.008	(0.039)	0.001	(0.035)
Prior class probability	0.381***	(0.034)	0.155***	(0.020)	0.465***	(0.031)
Observations in the class	5255		1605		5412	
Individuals in the class	1411		365		1398	

Notes. The dependent variable is the binary indicator for having insurance-covered healthcare expenditure. The table reports marginal effects for covariates and their robust standard errors, estimated using delta method, in parentheses. Marginal effects are evaluated at sample means. Group1, group2, group3, group4 and group5 denote dichotomous variables for log (income) quintiles, with group1 standing for the lowest quintile, and group5 indicating the highest quintile. Numbers of observations and clusters are based on the posterior assignment of each observation to the most probable latent class.

Table 5. Marginal effects in the binary choice equation for inpatient care: panel data finite mixture probit model

	Latent class 1 (low users)		Latent class 2 (high users)		Latent class 3 (median users)	
constant	–13.401***	(3.483)	0.044	(1.213)	–0.700	(0.684)
age	0.0001	(0.002)	0.006	(0.125)	–0.001	(0.034)
PDI	0.0001	(0.002)	–0.009	(0.102)	0.003	(0.039)
BMI	0.0005	(0.002)	–0.007	(0.159)	–0.003	(0.053)
group1 × log(income)	–0.002	(0.002)	–0.102	(0.147)	0.034	(0.052)
group2 × log(income)	0.007	(0.015)	0.809	(0.818)	–0.208	(0.223)
group3 × log(income)	–0.001	(0.019)	0.309	(1.142)	–0.045	(0.354)
group4 × log(income)	–0.001	(0.016)	0.437	(0.745)	–0.031	(0.316)
group5 × log(income)	0.001	(0.001)	0.010	(0.027)	–0.003	(0.011)
gender	0.0001	(0.001)	–0.171***	(0.049)	–0.015	(0.018)
education	–0.0002	(0.001)	–0.134***	(0.043)	0.036**	(0.016)
group1	0.999***	(0.004)	0.829**	(0.413)	–0.142	(0.092)
group2	–0.655	(1.711)	–1.000***	(9E–06)	1.000***	(3E–04)
group3	0.810	(8.576)	–0.722	(1.484)	0.735	(4.362)
group4	0.819	(4.971)	–0.921**	(0.423)	0.486	(3.32)
lowhcond	–0.001	(0.001)	0.269***	(0.068)	0.138***	(0.038)
smoking	0.003	(0.003)	–0.146***	(0.051)	0.010	(0.02)
drinking	0.001	(0.002)	0.062	(0.05)	–0.060***	(0.018)
NHI	–0.0004	(0.001)	0.025	(0.049)	–0.003	(0.017)
work	0.001	(0.001)	–0.115*	(0.062)	–0.118***	(0.028)
designated	0.008	(0.007)	–0.142***	(0.058)	0.020	(0.031)
city	0.001	(0.001)	–0.108*	(0.06)	0.015	(0.009)
Prior class probability	0.477***	(0.046)	0.194***	(0.048)	0.329***	(0.053)
Observations in the class	10105		647		1520	
Individuals in the class	2694		160		320	

Notes. The dependent variable is the binary indicator for using inpatient care and having out-of-pocket healthcare expenditure within health insurance. The table reports marginal effects for covariates and their robust standard errors, estimated using delta method, in parentheses. Marginal effects are evaluated at sample means. Group1, group^2, group^3, group4 and group5 denote dichotomous variables for log (income) quintiles, with group1 standing for the lowest quintile, and group5 indicating the highest quintile. Numbers of observations and clusters are based on the posterior assignment of each observation to the most probable latent class.

*** — $p < 0.01$, ** — $p < 0.05$, * — $p < 0.1$.

Other variables, which explain the use of healthcare are: education, poor health (lowhcond), and risky habits (smoking and drinking).

High users of any healthcare constitute 38.1 percent of sample and the mean value of the binary dependent variable in this class is 0.96 (standard deviation, SD = 0.19). This may be contrasted to the mean values of 0.09 (SD = 0.28) in the class of low users and 0.52 (SD = 0.50) in the class of median users. On average, most frequent users are less healthy than consumers in the low or median use categories: the mean value of lowhcond is 0.133 across high users (SD = 0.34), while the mean values at other two classes are 0.083 (SD = 0.28).

The inpatient care is less prevalent in Japan than in other OECD countries, so the class of frequent users is only 19.4% of the sample. As may be seen from Table 5, the demand for inpatient care is pro-poor for high and low users, and equitable for median users. The values of lowhcond are average 0.22 across high users (SD = 0.41), 0.17 across median users (SD = 0.38) and 0.09 across low users (SD = 0.28).

5.2. Modeling healthcare expenditure with logged dependent variable

The errors in the loglinear models for outpatient or inpatient healthcare expenditure are nonnormal but homoscedastic. The fact is similar to the results of earlier studies on the applicability of normal mixtures for predicting healthcare costs (Besstremyannaya, 2015) and enables the use of Duan's (1983) smearing factor for post-estimation analysis.

However, experimenting with generalized linear models for several distribution families we discover that the model with the exponential distribution outperforms the loglinear model in terms of mean squared error (MSE) and mean absolute prediction error (MAPE) of outpatient healthcare expenditure. The results of the residual analysis and goodness-of-fit statistics for these two models are presented in Table 6. The model with three classes and the exponential distribution is most preferable in terms of residual analysis and the values of AIC. The loglinear model with four classes gives slightly smaller values of the bias, MAPE and MSE than the three-class model. However, the value of the log likelihood statistics is higher for the four-class model and the four-class model would not pass the Greene (2007) test if compared to the three-class model. To sum up, the models with three latent classes provide the best fit both in case of the loglinear model and the model with the exponential distribution family. The Appendix gives model comparison for the Weibull and gamma distribution families, which underperform the model with the exponential distribution.

Table 6. Comparison of the panel data finite mixture models for outpatient healthcare expenditure

	Loglinear model				Exponential glm			
	Fmm-1	Fmm-2	Fmm-3	Fmm-4	Fmm-1	Fmm-2	Fmm-3	Fmm-4
Bias (residual)	–1.38	–1.64	**–0.58**	–0.37	0.08	3.42	**3.78**	28.32
MAPE	40.35	34.01	**30.91**	29.99	40.11	32.25	**28.94**	36.26
MSE	8987.71	8115.76	**7395.54**	7371.77	8958.82	7234.76	**5965.25**	9927.96
log *L*	–10959.5	–10311.6	**–10061.0**	–9921.59	–35797.4	–34965.5	**–34830.1**	–34794.7
AIC	21961.1	20717.2	**20264.1**	20033.2	71638.8	70020.9	**69796.1**	69771.5

Notes. Fmm-1 denotes the models without latent classes. Fmm-2, Fmm-3 and Fmm-4 indicate models with two, three and four latent classes, respectively. MAPE is mean absolute prediction error. AIC = $-\log L + 2k$, where k is the number of parameters. Statistics for the preferred latent class models are in bold.

There are only 597 consumers with inpatient healthcare expenditure. Therefore, the analysis exploits at most two latent classes. The results of the model comparison, which are shown in Table 7, reveal that the generalized linear models with Weibull or gamma distribution families do not provide superior fit in comparison with the loglinear model. The generalized linear model with the exponential distribution family and two latent classes has the insignificant prior probability for the second class, so the model is not used in our analysis.

Accordingly, we choose the loglinear model and conduct estimations both without latent classes and with two latent classes. The reason is the inability to fully prefer the two-class model to the model without latent classes due to the failure of the Greene (2007) likelihood ratio test.

Table 7. Comparison of the panel data finite mixture models for inpatient healthcare expenditure

	Loglinear model		Gamma glm		Weibull glm	
	Fmm-1	Fmm-2	Fmm-1	Fmm-2	Fmm-1	Fmm-2
Bias (residual)	–8.67	12.50	–1.35	235.64	99.11	110.76
MAPE	162.27	128.85	158.01	236.62	149.75	201.28
MSE	67357.78	53810.06	64748.85	124682.5	74745.15	83325.98
log L	–879.39	–804.54	–3821.19	–3758.76	–3824.30	–3777.42
AIC	1804.8	1703.1	7688.4	7611.5	7694.6	7648.8

Notes. Fmm-1 denotes the models without latent classes. The shape parameter in the generalized linear model without latent classes and Gamma distribution family is not statistically different from unity, so the goodness of fit statistics are close to those for Fmm-1 in the model with the exponential distribution. Fmm-2, Fmm-3 and Fmm-4 indicate models with two, three and four latent classes, respectively. MAPE is mean absolute prediction error. AIC $= -\log L + 2k$, where k is the number of parameters. Statistics for the preferred latent class models are in bold. Fmm-3 and Fmm-4 are not estimated for inpatient expenditure due to relative small sample sizes.

5.3. Income equity in the models with latent classes

The coefficients for income groups are insignificant in each of the latent classes in the log-linear model for outpatient care (Table 8). This implies that different from the findings for the binary choice models, healthcare utilization proxied by expenditure, is equitable. The findings on horizontal equity with respect to income in Japan may be contrasted to the estimations of log healthcare expenditure of the US elderly, where the coefficients for the lowest income quartile are significant in each latent class (Deb, Trivedi, 2013).

The exponential GLM applied to outpatient care similarly reveals insignificance of the coefficients for income quintiles. However, the standard errors for the income group coefficients are overly high in this model, which casts doubts on the convergence of the maximum-likelihood algorithm and hence, validity of division into income groups.

Concerning inpatient care, the results of the estimations reveal insignificance of the coefficients for income groups in the model without latent classes. As for the model with latent classes, the coefficient for the lowest income quantile is negatively significant at the 10% level in the class of frequent users (Table 9).

5.4. Overview of results

Our analysis used a mixture of distributions for modelling healthcare utilization and use. The approach treats the universe of consumers as several groups, and assumes a group-specific distribution of the binary choice decision and utilization decision. The separation into groups

Table 8. Estimating healthcare expenditure with a finite mixture panel data loglinear model, consumers who used only outpatient care

	Latent class 1 (high users)		Latent class 2 (median users)		Latent class 3 (low users)	
constant	1.838***	(0.374)	2.001***	(0.178)	1.058***	(0.19)
age	0.025***	(0.002)	0.036***	(0.001)	0.028***	(0.001)
Psychological distress index	0.005	(0.006)	–0.010***	(0.003)	–0.003	(0.003)
Body mass index	0.047***	(0.008)	0.018***	(0.004)	0.016***	(0.005)
group1 × log(income)	–0.028	(0.148)	–0.094*	(0.055)	0.079	(0.068)
group2 × log(income)	0.673	(0.579)	–0.708**	(0.28)	–0.154	(0.31)
group3 × log(income)	0.719	(1.273)	–0.364	(0.564)	–0.6914	(0.67)
group4 × log(income)	1.306**	(0.56)	–0.108	(0.339)	–0.492	(0.386)
group5 × log(income)	0.009	(0.022)	–0.011	(0.013)	0.003	(0.012)
gender	0.079	(0.065)	–0.094***	(0.028)	–0.091***	(0.035)
education	0.061	(0.057)	–0.168***	(0.026)	–0.003	(0.031)
group1	0.055	(1.126)	0.623	(0.416)	–0.710	(0.51)
group2	–5.731	(4.732)	5.726**	(2.285)	1.19	(2.524)
group3	–6.105	(10.754)	2.990	(4.772)	5.729	(5.665)
group4	–11.315**	(4.895)	0.838	(2.955)	4.285	(3.369)
lowhcond	0.452***	(0.093)	0.329***	(0.04)	0.470***	(0.059)
smoking	–0.073	(0.078)	0.240***	(0.031)	–0.075**	(0.037)
drinking	–0.196***	(0.061)	0.097***	(0.028)	–0.052	(0.033)
NHI	–0.033	(0.066)	–0.129***	(0.032)	–0.069*	(0.039)
work	–0.253***	(0.069)	–0.124***	(0.034)	–0.042	(0.038)
designated	0.123	(0.109)	–0.171***	(0.048)	0.047	(0.053)
city	–0.058	(0.101)	–0.089**	(0.044)	–0.037	(0.048)
Prior class probability	0.262***	(0.017)	0.245***	(0.015)	0.493***	(0.015)
Observations in the class	1713		2134		3573	
Individuals in the class	495		737		1349	

Notes. The dependent variable is logarithm of out-of-pocket healthcare expenditure within health insurance for the subsample that used only outpatient care. The eable reports coefficients for covariates and robust standard errors in parentheses. Group1, group2, group3, group4 and group5 denote dichotomous variables for log (income) quintiles, with group1 standing for the lowest quintile, and group5 indicating the highest quintile.

*** — $p < 0.01$, ** — $p < 0.05$, * — $p < 0.1$.

is conducted according to the unobserved variable (s), which justifies the applicability of the mixture (latent class) models. It should be noted that the methodology may be viewed as an applicable alternative for the subjective division into groups, according to arbitrary chosen criteria by healthcare analysts.

The paper uses the probit model with the three latent classes for estimating the binary decision of healthcare utilization. We compared the fit of models with different number of classes, and chose the best model using the information criterion. The three classes may be interpreted as the low, median and high users of healthcare. The interpretation is based on the mean percent of the unity values of the dependent variable in each group. Indeed, as the separation into

Table 9. Estimating healthcare expenditure with panel data loglinear model, consumers who used inpatient care

	Whole sample		Latent class model			
			Latent class 1 (high users)		Latent class 2 (low users)	
constant	5.242***	(0.501)	5.615***	(0.476)	4.553***	(1.244)
age	0.021***	(0.004)	0.009***	(0.003)	0.027***	(0.01)
Psychological distress index	0.004	(0.009)	–0.013	(0.009)	0.019	(0.024)
Body Mass Index	–0.036***	(0.007)	0.011	(0.011)	–0.058**	(0.023)
group1 × log(income)	0.061	(0.148)	0.127	(0.115)	–0.013	(0.398)
group2 × log(income)	1.189	(0.823)	–1.131*	(0.628)	8.164***	(2.118)
group3 × log(income)	0.074	(2.253)	1.058	(1.76)	–4.070	(5.13)
group4 × log(income)	–1.151	(1.483)	0.242	(1.194)	–2.68	(4.37)
group5 × log(income)	–0.053	(0.034)	–0.026	(0.032)	–0.156*	(0.082)
gender	–0.226**	(0.105)	–0.228**	(0.094)	–0.085	(0.264)
education	0.051	(0.093)	0.001	(0.085)	0.252	(0.236)
group1	–0.914	(1.118)	–1.583*	(0.872)	–0.106	(3.04)
group2	–10.167	(6.702)	8.491*	(5.127)	–67.13***	(17.345)
group3	–1.027	(19.072)	–9.438	(14.921)	33.873	(43.346)
group4	9.633	(12.939)	–2.579	(10.393)	22.906	(38.013)
lowhcond	0.361***	(0.116)	0.009	(0.112)	0.928***	(0.261)
smoking	–0.080	(0.124)	–0.119	(0.095)	–0.246	(0.322)
drinking	–0.179*	(0.094)	–0.347***	(0.084)	0.234	(0.229)
NHI	–0.259**	(0.105)	–0.063	(0.09)	–0.577**	(0.288)
work	–0.152	(0.106)	–0.107	(0.095)	–0.248	(0.245)
designated	0.140	(0.149)	0.362**	(0.142)	–0.250	(0.354)
city	0.076	(0.131)	0.164	(0.132)	–0.044	(0.289)
Prior class probability			0.597***	(0.049)	0.403***	(0.049)
Observations in the class	597		426		171	
Individuals in the class			331		136	

Notes. The dependent variable is logarithm of out-of-pocket healthcare expenditure within health insurance for the subsample that used inpatient care. The table reports coefficients for covariates and robust standard errors in parentheses. Group1, group2, group3, group4 and group5 denote dichotomous variables for log (income) quintiles, with group1 standing for the lowest quintile, and group5 indicating the highest quintile.

*** — $p < 0.01$, ** — $p < 0.05$, * — $p < 0.1$.

groups is not subjective, each observation is assigned to a latent class according to the posterior class probability (Greene, 2007).

The models with three latent classes are used for analyzing the continuous positive variable of healthcare expenditure. The results of the estimates come from the generalized linear models with lognormal and exponential distribution. The generalized linear models allow solving the retransformation problem of logged dependent variable (Nelder, Weddernburn, 1972; McCullagh, Nelder, 1989). It may be noted that the sole use of information criteria may not be well applicable for the models with the continuous dependent variable, so the choice of the best model was based on the mean standard error and mean absolute prediction error.

The results of the estimates may be summarized as follows. Firstly, the fact of seeking healthcare depends on consumer income. In particular, there is a bias towards the lowest income groups, so healthcare access is pro-poor. Secondly, the analysis of outpatient healthcare expenditure shows the absence of income bias. In other words, healthcare use does not depend on the income quintile. Finally, there is income inequity for healthcare expenditure in hospitals, and this inequity is anti-poor in the group of most frequent users.

5.5. Robustness and limitations

Our discussion of robustness of estimates touches upon several data issues. Firstly, there is attrition bias in the Japan Household Panel Survey, which is similar to other longitudinal consumer surveys and may be explained by non-response or migration of respondents. However, the panel is only weakly unbalanced. For instance, 76% of observations for all ages and 72% of observations for non-elderly consumers appear across all periods of time. Comparing the descriptive statistics for different waves of the survey, we do not find any systematic bias in terms of the values of the dependent and explanatory variables.

Secondly, this paper follows the earlier approaches in the analysis of healthcare demand in Japan and exploits the disposable income, reported by consumers. Although non-reporting or misreporting of income by median and high-income categories might be a problem with other consumer surveys, we do not believe this is the issue with Japanese respondents. In a formal robustness check we impute the total consumer expenditure by adding various expenditure categories. The imputed expenditure is often used as a proxy of income in absence of reliable data with consumer surveys of other countries. It should be noted that the values of income and imputed expenditure in the Japan Household Panel Survey are not fully comparable due to potential recall bias: expenditure are asked on a monthly basis while income is reported annually. Nonetheless, it is plausible to assume that the recall bias would not differ across income groups. Accordingly, we project the expenditure for the 12-month period and contrast it to the reported income. As a result, there is no underreporting of income by median and high-income quantiles.

The major limitation of our analysis, however, is the approximation of the low income category by the lowest quintile. Indeed, the knowledge about the poverty line in municipality would enable more accurate estimates. Finally, small sample size of inpatient care users allows only tentative conclusions about income equity of their healthcare demand.

6. Discussion

Our estimations, which account for unobservable consumer heterogeneity through a latent class approach, reveal that healthcare access is pro-poor for the most sick Japanese consumers. Outpatient healthcare utilization in terms of healthcare expenditure is fully equitable with respect to household income. The findings are similar to equitable or pro-poor non-specialist care utilization in OECD countries (van Doorslaer et al., 2004). However, there are other aspects where Japanese social health insurance system may demonstrate income inequity: health insurance premiums and catastrophic coverage (Ikegami et al., 2011; Hashimoto et al., 2011; Health and Global…, 2009).

We use the data of Japan Household Panel Survey to estimate the share of National Health Insurance (NHI) premiums in the disposable household income (for single non-elderly respondents). The resulting figure is 9.06%, which is twice higher than the corresponding value for the users of the company-based insurance. The differences in the burden of premiums in the disposable household income reveal income inequity for the users of the two health insurance plans. According to Ikegami et al. (2011), the reason is relatively low average income and relatively high health risk of enrollees in National Health Insurance, who are retirees, unemployed, and self-employed.

Second, using our data we discover horizontal inequity of premiums within the subscribers of National Health Insurance: the premiums constitute 14% of income for the lowest quintile, which is 3–4 times higher than the figures for higher income groups (Figure 1). The differences in the share of premiums in household income between income quintiles are statistically significant. Overall, horizontal inequity in premiums is common in the developed countries with social health insurance (Wagstaff, 2010). Yet, a solution to the problem of intra-health insurance plans and within-NHI plan inequity in premiums in Japan may be found in the consolidation of municipal NHI plans at the prefectural level, which would raise healthcare efficiency, increase the degree of solidarity, and lower the existing inequity in premiums (Ikegami et al., 2011; Hashimoto et al., 2011).

Finally, our analysis of the prevalence of high-cost medical benefits reveals that the catastrophic coverage is not necessarily equitable or pro-poor. Indeed, the shares of consumers who applied for high-cost medical benefits are the highest in the top quintile and the second quintile. The differences between the fifth quintile and quintiles 1, 3, and 4 are statistically significant. Presumably, higher prevalence of using high-cost medical benefits in the top income quin-

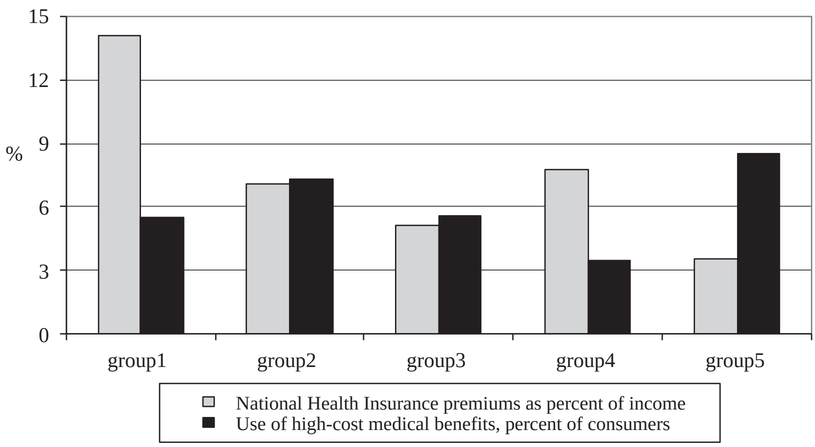

Fig. 1. Share of premium in household income and prevalence of applying for catastrophic coverage by income quintile (non-elderly consumers)

Source: Estimations according to Japan Household Panel Survey (2009).
Note. The share of premium in household income could be estimated only for single respondents in National Health Insurance.

tile is explained by higher healthcare expenditure these consumers can afford. At the same time, Japanese consumers of the top income quintile may have better knowledge about the system of catastrophic coverage[13].

7. Conclusion

The paper studies horizontal equity in healthcare access and utilization in Japan by estimating the coefficients for income groups in the Duan et al.'s (1983) multi-part model which distinguishes between non-users, the users of inpatient and outpatient care. To account for consumer unobservable characteristics, we apply a latent class approach (Deb, Trivedi, 1997). We address a retransformation problem in the equations with logarithm of healthcare expenditure as dependent variable, using Greene's (2007) generalized linear models with latent classes.

Our sample is six waves of data for healthcare expenditure by the Japan Household Panel Survey. The results prove the applicability of latent class models to account for heterogeneity in healthcare access and utilization in Japan. Namely, consumers separate into latent classes in the binary choice models for healthcare use and generalized linear models for outpatient/inpatient healthcare expenditure. The paper discovers a pro-poor horizontal inequity in healthcare access with respect to disposable income in Japan. Healthcare utilization is fully equitable, but certain income inequity may be revealed in the amounts of health insurance premiums and the prevalence of catastrophic coverage.

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References

Babazono A., Kuwabara K., Hagihara A. (2008). Does income influence demand for medical services despite Japan's «healthcare for all» policy? *International Journal of Technology Assessment in Healthcare*, 24 (1), 125–130.

Basu A., Manning W. G. (2009). Issues for the next generation of healthcare cost analyses. *Medical Care*, 47 (7), S109–114.

Ben-Sira Z. (1982). The scale of psychological distress (SPD): Crosspopulational invariance and validity. *Research Communications in Psychology, Psychiatry and Behavior*, 7 (3), 329–346.

Bessho S., Ohkusa Y. (2006). When do people visit a doctor? *Healthcare Management Science*, 9, 5–18.

Baldi I., Pagano E., Berchialla P., Desideri A., Ferrando A., Merletti F., Gregori D. (2013). Modeling healthcare costs in simultaneous presence of asymmetry, heteroscedasticity and correlation. *Journal of Applied Statistics*, 40, 298–310.

[13] Overall, Japanese consumers have very limited knowledge about the system of high-cost medical benefits: the results of January 2009 survey of 1016 respondents by Japan's Health and Global Policy Institute indicate that 18.7% do not know anything at all about the system; 25.7% have heard the name of the system but do not know anything about how the system works; 41% know about the essence of the system to some extent; and only 13.9% admit they have sufficient knowledge of the system (Health and Global…, 2009).

Besstremyannaya G. (2012). Estimating income equity in social health insurance system. *CEFIR/NES Working Papers*, WP 172.

Besstremyannaya G. (2015). Heterogeneous effect of coinsurance rate on healthcare expenditure: Generalized finite mixtures and matching estimators. *Applied Economics*, 47 (58), 6331–6361.

Blough D. K., Madden C. W., Hornbrook M. C. (1999). Modeling risk using generalized linear models. *Journal of Health Economics*, 18, 153–171.

Buntin M. B., Zaslavsky A. M. (2004). Too much ado about two-part models and transformation? Comparing methods of modeling Medicare expenditures. *Journal of Health Economics*, 23, 525–542.

Cameron A. C., Trivedi P. K. (2013). *Regression analysis of count data*. 2nd edition. Cambridge University Press, 2013.

Culyer A. J. (2005). *The dictionary of health economics.* Edward Elgar.

Culyer A. J., Wagstaff A. (1993). Equity and equality in health and healthcare. *Journal of Health Economics*, 12, 431–457.

Cutler D. M. (2002). Healthcare and the public sector. In: Auerbach A. J., Feldstein M. (eds.), *Handbook of Public Economics*, Vol. 4. Elsevier Science, 2145–2243.

Deb P., Burgess J. (2003). A quasi-experimental comparison of econometric models for healthcare expenditures. *Hunter College Department of Economics Working Papers* 212, City University of New York.

Deb P., Holmes A. M. (2000). Estimates of use and costs of behavioral healthcare: A comparison of standard and finite mixture models. *Health Economics*, 9, 475–489.

Deb P., Trivedi P. K. (1997). Demand for medical care by the elderly: A finite mixture approach. *Journal of Applied Econometrics*, 12, 313–336.

Deb P., Trivedi P. K. (2013). Finite mixture for panels with fixed effects. *Journal of Econometric Methods*, 2 (1), 35–51.

Duan N. (1983). Smearing estimate: A nonparametric retransformation method. *Journal of the American Statistical Association*, 78 (383), 605–610.

Duan N., Manning W. G., Morris C. N., Newhouse J. P. (1983). A comparison of alternative models for the demand for medical care. *Journal of Business and Economic Statistics*, 1 (2), 115–126.

Gravelle H., Morris S., Sutton M. (2006). Economic studies of equity in the consumption. In: Jones A. M. (ed.), *The Elgar Companion to Health Economics*. Edward Elgar Publishing, 193–204.

Greene W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, 126 (2), 269–303.

Greene W. (2007). *LIMDEP version 9.0. Econometric modelling guide*. V. 1–2. Econometric Software, Australia.

Hashimoto H., Ikegami N., Shibiya K., Izumida N., Noguchi H., Miyata H., Acuin J. M., Reich M. (2011). Cost containment and quality of care in Japan: Is there a trade-off? *Lancet*, 378, 1174–1182.

Health and Global Policy Institute (2009). Nihon iryou-nikansuru 2009 nen yoronchousa (gaiyou dai ni ban) February, 25. http://www.hgpi.org/handout/2009-10-02_45_524645.pdf (in Japanese).

Heckman J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47 (1), 153–161.

Hurley J. (2000). An overview of the normative economics of health sector. In: Culyer A. J. and Newhouse J. P. (eds.), *Handbook of Health Economics*, Vol. 1. Elsevier, 56–117.

Ii M., Ohkusa Y. (2002). Price sensitivity of the demand for medical services for minor ailments: econometric estimates using information on illnesses and symptoms. *The Japanese Economic Review*, 53 (2), 154–166.

Ikegami N. (2005). Japan. In: Gauld R. (ed.), *Comparative Health Policy in the Asia–Pacific*. Open University Press, England, 122–145.

Ikegami N. (2006). Should providers be allowed to extra bill for uncovered services? Debate, resolution, and sequel in Japan. *Journal of Health Politics, Policy and Law*, 31 (6), 1129–1149.

Ikegami N., Campbell J. (1999). Healthcare reform in Japan: The virtues of muddling through. *Health Affairs*, 19 (3), 56–75.

Ikegami N., Campbell J. (2004). Japan's healthcare system: containing costs and attempting reform. *Health Affairs*, 23 (3), 26–36.

Ikegami N., Yoo B. K., Hashimoto H., Matsumoto M., Ogata H., Babazono A., Watanabe R., Shibuya K., Yang B. M., Reich M. R., Kobayashi Y. (2011). Japanese universal health coverage: Evolution, achievements, and challenges. *Lancet*, 378, 1106–1115.

Imai Y. (2002). Healthcare reform in Japan. *OECD Working Papers*, ECO/WKP/ (2002) 7.

Ishii K. (2011). Keizaiteki chii to iryou saabisuno riyo (Economic status and healthcare utilization). In: Higuchi Y., Miyauchi T., McKenzie C. R. (eds.), *Kyouiku kenkou to hinkon no dainamizumu* (Education, Health and Dynamics of poverty). Keio University, Tokyo, v117–130 (in Japanese).

Jones A. M., Wildman J. (2008). Health, income and relative deprivation: Evidence from the BHPS. *Journal of Health Economics*, 27, 308–324.

Jones A. M., Lomas J., Moore P., Rice N. (2013). A quasi-Monte Carlo comparison of developments in parametric and semi-parametric regression methods for heavy tailed and non-normal data: With an application to healthcare costs. *HEDG Working Paper* 13/30. The University of York, York.

Kawai H. (2007). Shakai keizai kakusa to kenkou kakusa (Socio-economic inequality and health inequality). In: Higuchi Y. (ed.), *Nihon-no kakei-no dainamizumu* (Dynamics of Japanese Households) [III]. Keio University, Tokyo, 239–261 (in Japanese).

Kawai H. (2010). Shintaiteki seishinteki kenkou ga iryouhi to shotoku ni ataeru eikyou (The effect of body and mental health on healthcare expenditure and income). In: Higuchi Y., Miyauchi T., McKenzie C. R. (eds.), *Hinkon no dainamizumu* (Dynamics of Poverty). Keio University, Tokyo, 153–169 (in Japanese).

Kupor S. A., Liu Y. C., Lee J., Yoshikawa A. (1995). The effect of co-payments and income on the utilization of medical care by subscribers to Japan's National Health Insurance system. *International Journal of Health Services*, 25 (2), 295–312.

Manning W. G., Mullahy J. (2001). Estimating log models: To transform or not to transform? *Journal of Health Economics*, 20, 461–494.

Manning W. G. (1998). The logged dependent variable, heteroscedasticity, and the retransformation problem. *Journal of Health Economics*, 17, 283–295.

McCullagh P., Nelder J. A. (1989). *Generalized linear models*, 2nd edition. Chapman and Hall.

Mihaylova B., Briggs A., O'Hagan A., Thompson S. G. (2011). Review of statistical methods for analyzing healthcare resources and costs. *Health Economics*, 20, 897–916.

Ministry of Health, Labor, and Welfare. (2011). Heisei 18nen iryou seido kaikaku-kanren shiryou, Kougaku iryou, kougaku kaigo gassan ryouyouhi seido-nitsuite, Sanko shiryou [Materials related to the reform in healthcare system in heisei 18]. http://www.mhlw.go.jp/bunya/shakaihosho/iryouseido01/pdf/tdfk02-03-02.pdf (in Japanese).

Mullahy J. (1998). Much ado about two: Reconsidering retransformation and the two-part model in health econometrics. *Journal of Health Economics*, 17, 247–281.

Mullahy J. (2009). Econometric modeling of healthcare costs and expenditures. A survey of analytical issues and related policy considerations. *Medical Care*, 47 (7), S104–108.

Nelder J. A., Wedderburn W. M. (1972). Generalized linear models. *Journal of the Royal Statistical Society, Series A (General)*, 135 (3), 370–384.

Newhouse J. P., Manning W. G., Morris C. N., Orr L. L., Duan N., Keeler E. B., Leibowitz A., Marquis K. H., Marquis M. S., Phelps C. E., Brook R. H. (1981). Some interim results from a controlled trial of cost sharing in health insurance. *New England Journal of Medicine*, 305 (25), 1501–1507.

Nishimura S. (1987). Ishi yuuhatsu juyou riron-wo megutte (Chapter 3. On the theory of physician-induced demand). In: Nishimura S. (ed.), *Iryou-no keizai bunseki* (Economic Analysis of Healthcare). Tokyo, Toyo keizai shimposha, 25–46 (in Japanese).

Nyman J. A. (2006). The value of health insurance. In: Jones A. M. (ed.), *The Elgar Companion to Health Economics*. Edward Elgar Publishing, 95–103.

OECD (2009). Health-care reform in Japan: Controlling costs, improving quality and ensuring equity. In*: OECD Economic Surveys: Japan 2009*, Chapter 4, 99–133.

Rannan-Eliya R., Somanathan A. (2006). Equity in health and healthcare systems in Asia. In: Jones A. M. (ed.), *The Elgar Companion to Health Economics.* Edward Elgar Publishing, 205–218.

Sawano K. (2001). Gairai iryousabisu-niokeru iryoukyoukyuu-no yakuwari. Showa 59 nen to heisei 9 nen kaitei-no chigai to sono riyuu (Access to hospital and the demand for ambulatory care services in Japan). *Osaka daigaku keizai gaku*, 50 (4), 26–40 (in Japanese).

Senoo Y. (1985). Iryouhi yokoseisaku-no keizai bunseki (Economic analysis of healthcare cost containment). In: *Iryou sisutemu ron* (The Theory of Healthcare System). Tokyo, Toukyou daigaku shuppansha, 127–148 (in Japanese).

Tokuda Y., Ohde S., Takahashi O., Hinohara S., Fukui T. (2009). Influence of income on health status and healthcare utilization in working adults: An illustration of health among the working poor in Japan. *Japanese Journal of Political Science*, 10 (1), 79–92.

Van Doorslaer E., Masseria C., and the OECD Health Equity Research Group Members (2004). Income-related inequality in the use of medical care in 21 OECD countries. *OECD Health Working Papers* 14, DELSA/ELSA/WD/HEA (2004) 5.

Wagstaff A. (2010). Social health insurance reexamined. *Health Economics*, 19, 503–517.

Wagstaff A., van Doorslaer E., Paci P. (1991a). Horizontal inequity in the delivery of healthcare. *Journal of Health Economics*, 10 (2), 251–256.

Wagstaff A., van Doorslaer E., Paci P. (1991b). On the measurement of horizontal inequity in the delivery of healthcare. *Journal of Health Economics*, 10 (2), 169–205.

Wagstaff A., van Doorslaer E. (2000a). Measuring and testing for inequity in the delivery of healthcare. *The Journal of Human Resources*, 35 (4), 716–733.

Wagstaff A., van Doorslaer E. (2000b). Equity in healthcare finance and delivery. In: Culyer A. J., Newhouse J. P. (eds.), *Handbook of Health Economics*. Elsevier, 1803–1862.

Yamada T. (1997). Iryou sabisu-no juyou-nitsuite (On the demand for medical care). *Iryou to shakai* 7 (3), 99–112 (in Japanese).

Zweifel P., Breyer F. (2006). The economics of social health insurance. In: Jones A. M. (ed.), *The Elgar Companion to Health Economics*. Edward Elgar Publishing, 126–135.

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Appendix

Table A1. Comparison of the generalized linear models for outpatient healthcare expenditure

	Gamma distribution family				Weibull distribution family			
	Fmm-1	Fmm-2	Fmm-3	Fmm-4	Fmm-1	Fmm-2	Fmm-3	Fmm-4
Bias (residual)	0.08	50.51	50.43	50.37	–26.83	11.17	5.03	–14.36
MAPE	40.11	50.51	50.42	50.37	5.42	35.33	52.86	76.55
MSE	8958.82	12039.93	12035.73	12033.45	9954.37	7705.28	12528.24	46038.35
log L	–35797.4	–34630.7	–35797.4	–34002.8	–35701.4	–34678.5	–34208.8	–34043.3
AIC	71638.8	69355.4	71638.8	68195.5	71448.8	69450.9	68559.6	68276.5

Notes. 1) Fmm-1 denotes the models without latent classes. The shape parameter in the generalized linear models without latent classes and Gamma distribution families is not statistically different from unity, so the estimates and the goodness of fit statistics coincide across the Fmm-1 model in this Table and Fmm-1 for the model with the exponential distribution.

2) Fmm-2, Fmm-3 and Fmm-4 indicate models with two, three and four latent classes, respectively.

3) MAPE is mean absolute prediction error.

4) AIC = $-\log L + 2k$, where k is the number of parameters.

Table A2. Studies estimating the effect of income on healthcare demand in Japan

Study	Demand variable	Sample	Income variable	Model	Income effect
Senoo (1985)	Utilization rate (per capita number of visits), average length of stay in inpatient, outpatient and dental care	Average data on national health insurance utilization for the 47 prefectures in 1980–1981	Per capita income	Cross-section models (for the years 1980 and 1981) and time series model for the years 1955–1979	Per capita income has a neutral effect on utilization rate in cross-section models, and positive and significant effect in time-series models
Nishimura (1987)	Cost per medical case in inpatient and outpatient care	Average data on national health insurance spending for the 47 prefectures in 1974–1983	Per capita income	Pooled data (simple OLS or the model with serial correlation)	Positive and significant income effect
Kupor et al. (1995)	Health insurance claims per 100 national health insurance members a year in inpatient, outpatient and dental care	Aggregated data, retrieved from the surveys of national health insurance users in the 47 prefectures in 1984 and 1989	Per capita income	Cross-section OLS regression in each of the two years	Positive and significant income effect for the aggregate healthcare utilization, for outpatient and for dental care
Yamada (1997)	Total cost a day in inpatient, outpatient and dental care	Claims data for the users of company-managed insurance, aged 20–59 in 1980–1995 (with exception of the year 1994)	Total income	OLS with annual dummies, analysis by gender	For men there is a positive and significant income effect for the cost of outpatient and dental care, and a neutral effect for the cost of inpatient care. For women there is a negative and significant income effect for the cost of inpatient care, and a neutral effect for the cost of outpatient or dental care
Sawano (2001)	Number of outpatient visits, total cost of healthcare (a sum of out-of-pocket payment and traveling cost to healthcare institution)	The average aggregated data for users of government-managed insurance in the 47 prefectures in 1983–1998	Average disposable income	Fixed effect panel data model	Insignificant effect
Ii, Ohkusa (2002)	Categorical variable, which equals 1 if a patient demands medical services; 2 if a patient buys over-the-counter medicines, and 0 otherwise	86 065 observations (people aged 22–59 who suffered from minor illnesses): the data are retrieved from the Comprehensive Survey of Living Standards run by MHLW in all 47 prefectures in 1986–1995	Labor income, net financial asset, real asset	Multinomial probit model, differences in probability	Insignificant effect

End of the table A2

Study	Demand variable	Sample	Income variable	Model	Income effect
Bessho, Ohkusa (2006)	Conditional probability of visiting a doctor on the *k*-th day since a person gets sick (a first consultation for acute minor illness)	1249 households of Tokyo metropolitan area (Tokyo, Kanagawa, Saitama and Chiba) surveyed in May 2001.	Household income; household financial assets	Sequential probit model	In case of cold: the coefficients for the dummy for household income group are higher in lower income groups than in middle-income groups. In case of headache: the coefficient for the dummy for household income is higher in middle-income groups than in lower and higher income groups
Kawai (2007)	Probability of demanding inpatient care, outpatient care, and buying drugs; probability of checkup	Data of Keio Household Panel Survey, 4000 respondents, waves of 2005 and 2006	Disposable income	OLS regressions	Insignificant income effect for inpatient and outpatient care: coefficients for the dummies for income groups are insignificant; negative income effect for checkups for lower income groups
Bazabono et al. (2008)	The average number of monthly bills per patient; the average number of service days per person; the average medical cost per person	1628 company-managed insurance societies in 2003 (aggregated data for 14 776 193 heads of households and 15 496 752 dependents)	Monthly salary	OLS regression	Outpatient and dental care: positive and significant income effect for average number of monthly bills per patient; the average number of service days per person; the average medical cost per person. Inpatient care: positive and significant income effect for the average medical cost per person, insignificant effect for average number of monthly bills per patient; the average number of service days per person.
Tokuda et al. (2009)	Visits to physicians, visits to pharmacy, use of complementary and alternative medicine	1406 working adults aged 20–65 out of a nationally representative household panel	Annual equivalent income	OLS regressions, income as a categorical explanatory variable	Insignificant effect of income
Kawai (2010)	Probability of visiting a doctor	Data of Japan Household Panel Survey, 4022 respondents, wave of 2009	Household income; household assets; household debt	Binary choice model	Insignificant effect of household income; positive effect of household assets; negative effect of household debt
Ishii (2011)	Probability of visiting a doctor; out-of-pocket healthcare expenditure	Data of Japan Household Panel Survey, 4022 respondents, waves of 2009 and 2010	Disposable household income	Probit model for utilization; OLS model for out-of-pocket expenditure	Positive and significant income effect for the probability of visiting a doctor: coefficients for the dummies for income quintiles are positive and significant in the subsample of consumers aged 20–39 (with the lowest income quintile as a reference group); generally insignificant income effect for the amount of out-of-pocket expenditure

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