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# **Estimating income equity in social health insurance system**

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# Estimating income equity in social health insurance system

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## Abstract

The paper measures horizontal equity in health care access and utilization in Japan by estimating the coefficients for income groups in a multi-part model which distinguishes between non-users of health care, the users of inpatient and outpatient care. To account for consumer unobservable characteristics, we apply a latent class approach. We address a retransformation problem of logged health care expenditure, using generalized linear models. Our sample is the 2009 data for 4,022 adult consumers (Japan Household Panel Survey). The coefficients for income groups are insignificant both in the binary choice models for inpatient/outpatient health care use, and in the models for health care expenditure. Consumers separate into two latent classes in the generalized linear model for outpatient health care expenditure. Although the results reveal horizontal equity in health care access and utilization in Japan, horizontal inequity remains in health insurance premiums and the prevalence of catastrophic coverage.

Keywords: health care demand, equity, income elasticity, generalized linear models, latent class, two-part model, four-part model, social health insurance

JEL codes: I10, I18, G22, R22

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# 1. Introduction

Guaranteeing equity for the poor is a major challenge for health care systems in developed countries. Overall, equity is an ethical issue related to the judgments about health care accessibility.<sup>2</sup> At the same time, an economic concept of horizontal equity deals with “an equal treatment for equal need” (Wagstaff and van Doorslaer, 1991a; Culyer and 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 and van Doorslaer, 1991b). In practical terms, there is a general agreement about striving for “minimal variation of [health care] use with income” (Newhouse et al., 1981) and ensuring equity for the poor (Wagstaff and 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 and 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 and Somanathan, 2006; Wagstaff, 2010). The most prevalent method for analyzing income equity measures coefficients for income groups in the equation for health care utilization, with equality of the coefficients interpreted as zero inequity (Wagstaff and van Doorslaer, 2000a; Jones and Wildman, 2008). The regression method should also be regarded as the most general. Indeed, the non-rejection of the null hypothesis of equality of coefficients for income groups provides a *sufficient* condition for zero inequity in terms of an alternative approach, which measures concentration indices (Wagstaff and van Doorslaer, 1991b; Wagstaff and van Doorslaer, 2000a; Wagstaff and van Doorslaer, 2000b). Regression method commonly regards the state of health as the major covariate that should have a significant estimated coefficient (i.e., *need* explanatory variable).<sup>3</sup> However, owing to limitations of most microdata surveys, qualitative parameters related to the state of health (e.g., self-assessed health) may fail to fully capture individual’s demand for health care. Therefore, incorporating consumer’s unobservable characteristics which influence the decision about health care use, as well as the amount

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<sup>2</sup> 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).

<sup>3</sup> Indeed, the healthy and the sick have different income elasticity of health care expenditure (Nyman, 2006).

of health care purchased, is essential for raising the precision of the estimations of health care demand.

The purpose of this paper is to estimate income equity in health care access and utilization in Japanese social health insurance system. Despite recent concerns about the poor in Japan, the findings on income effect for health care demand are limited and mixed. Income effect is insignificant according to the results of some studies (Senoo, 1985; Sawano, 2001; Ii and Ohkusa, 2002a; Kawai, 2007; Tokuda et al., 2009; Kawai, 2010), while other studies find a positive and significant income effect (Bessho and Ohkusa, 2006; Babazono et al., 2008; Ishii, 2011). The influence of income is commonly studied through estimating the significance of the coefficient for income variable, which might not be the most applicable approach since it captures only linear effects. Therefore, we follow papers that use dichotomous variables for income groups (Bessho and Ohkusa, 2006; Tokuda et al., 2009). Such approach, which incorporates non-linear income effects, allows a comparison of the values and significance of the coefficients for dichotomous variables of income groups relative to the reference group. Since poverty lines vary in each Japanese municipality (with municipality information unavailable in consumer survey data), we employ income quintiles (Ishii, 2011) so that the lowest quintile approximates the low income group (OECD, 2009).<sup>4</sup>

The novelty of the paper is twofold. First, we use the 2009 data for inpatient and outpatient health care expenditure by 4,022 adult consumers from Japan Household Panel Survey,<sup>5</sup> which enables an estimation of a multi-part model, distinguishing between non-users of health care, the users of inpatient and outpatient care (Duan et al., 1983). Second, we employ a latent class approach (Deb and Trivedi, 1997) that better encompasses unobservable consumer characteristics than subjective health assessment. The multi-part model comprises equations for the binary choice of seeking inpatient/outpatient care, as well as equations for the amount of inpatient/outpatient expenditure, given the expenditure is positive. The amount of health care expenditure is commonly taken in logarithms, to solve the issues of skewness and zero mass problem (i.e., the fact that health care expenditure is truncated at zero). Owing to the retransformation problem in equations with logged dependent variable (Duan et al., 1983; Manning, 1998; Mullahy, 1998), linear models can yield unbiased predictions only when error terms are normal or homoscedastic. A solution to the retransformation

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<sup>4</sup> Note that quintile analysis is commonly used in the studies of horizontal equity of OECD countries (van Doorslaer, 2004).

problem is the use of generalized linear models which specify the mean and variance functions of the dependent variable conditional on covariates (Nelder and Wedderburn, 1972; McCullagh and Nelder, 1989). Consequently, in case of non-normality and heteroscedasticity of error terms in OLS models for health care expenditure, we use Greene's (2007) generalized linear models with latent classes.

The results of our estimations indicate that the coefficients for income groups are insignificant both in the binary choice models for health care use and in the models for health care expenditure. Consumers separate into two latent classes in the generalized linear model for outpatient health care expenditure, and in the OLS model for health care expenditure of those who used inpatient care. In the generalized linear model we find adequate goodness-of-fit for the inverse Gaussian distribution family. As for binary choice models, consumers do not separate into latent classes. Overall, the results of the estimations reveal horizontal equity of health care access and utilization in Japanese health insurance system. However, horizontal inequity may be found in health insurance premiums and the prevalence of catastrophic health care coverage.

The remainder of the paper is structured as follows. Section 2 outlines various dimensions of equity in Japanese social health insurance system. Section 3 sets up the empirical models for measuring the demand for health care with need and non-need variables. Section 4 describes the data of Japan Household Panel Survey. The findings of the empirical estimations with the binary choice models, OLS 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 health care demand in Japan, derivations of deviance residuals and Anscombe residuals, normal probability plot for standardized deviance residuals, as well as details on the sampling procedure in Japan Household Panel Survey are presented in the Appendix.

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<sup>5</sup> The unique feature of this recently launched household survey is the fact that it distinguishes between inpatient and outpatient health care expenditure, as well as between expenditure covered and non-covered

## 2. Equity in Japanese social health insurance system

Mandatory and universal social health insurance system in Japan celebrates its semicentennial anniversary.<sup>6</sup> 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 choice of health care facilities, the size of nominal coinsurance rate, and the prices charged by providers.

The users of any health insurance plan can choose any health care institution, regardless of its location or type (e.g., private/public, hospital, clinic or ambulatory division of hospital). There are no gatekeepers, and only in 1996 an amendment to Health Insurance Law introduced minor payments for turning to a large facility without referral.<sup>7</sup>

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.<sup>8</sup> The schedule ensures equal prices for similar types of health care institutions.

The size of nominal coinsurance rate for non-elderly and non-infant population (aged 3-69) varied in the 0-50% interval, and became a flat value of 30% for enrollees of all health insurance plans since 2003 (Figure 1).

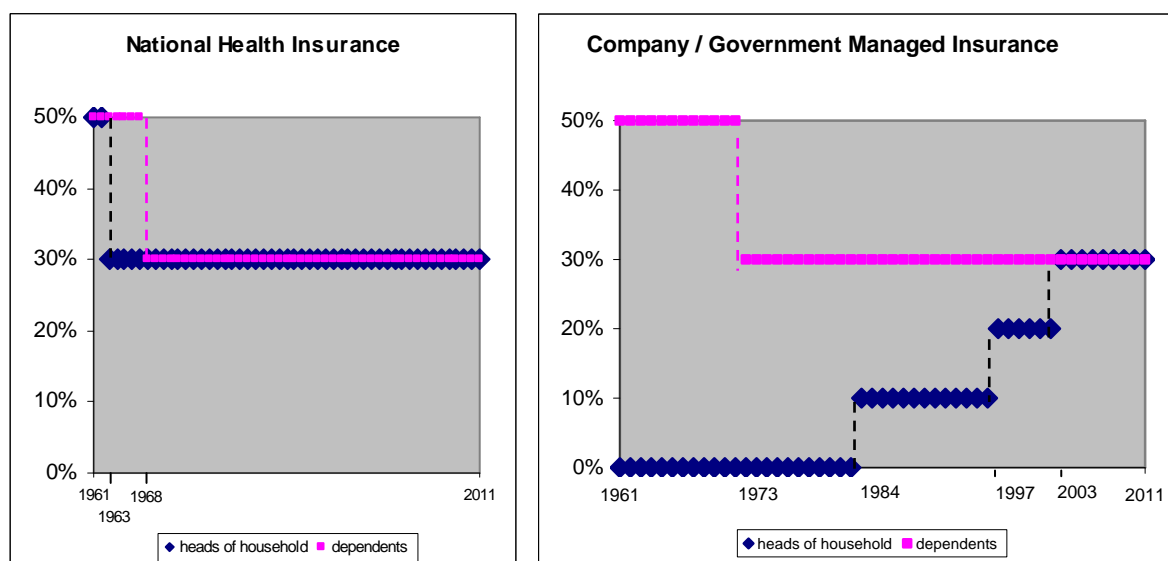
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by social health insurance.

<sup>6</sup> See the series "*Japan: Universal Health Care at 50 Years*" in *Lancet's* issue of September 17, 2011.

<sup>7</sup> A payment for the first visit to a large hospital (with over 200 beds) without referral would normally vary from 1,570 yen to 5,250 yen.

<sup>8</sup> 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 and Campbell, 2004), is prohibited in Japan (Ikegami, 2006).



**Figure 1. Nominal coinsurance rates in 1961-2011**

Note: Nominal coinsurance rate for inpatient care of dependents was 20% in 1980-2003.

Although consumers pay out-of-pocket for the incurred health care costs according to the nominal coinsurance rate, they are compensated by their insurer in case of high-cost medical expenditure. The system of high-cost medical benefits (catastrophic coverage) aims at enhancing income equity in health care access and utilization. Based on the amount of household income, consumers are compensated so that their nominal coinsurance rate become only 1% after a certain threshold value of incurred health care expenditure. As for the lowest income category, consumers face the cap of 35,400 yen a month, receiving the rest of the health insurance care for free (Table 1). Owing to the system of high-cost medical benefits, the values of the actual share of out-of-pocket expenditure incurred by an enrollee (effective coinsurance rate) are almost twice lower than the nominal coinsurance rate (Ikegami and Campbell, 1999; Imai, 2002; Ikegami and Campbell, 2004; Ikegami, 2005).

**Table 1. High-cost medical benefits (catastrophic coverage) for Japanese consumers aged 3-69**

| Income category                          | Caps on monthly out-of-pocket health insurance expenditure               |
|--|--|
| High income (above 530,000 yen a month)  | 150,000 yen + (health care expenditure – 500,000 yen)*1%<br><83,400 yen> |
| General category                         | 80,100 yen + (health care expenditure – 267,000 yen)*1%<br><44,400 yen>  |
| Low income (exempt from residence taxes) | 35,400 yen<br><24,600 yen>   |

Source: MHLW (2011), “Heisei 18nen iryou seido kaikaku-kanren shiryō, Kougaku iryō, kougaku kaigo gassan ryouyouhi seido-nitsuite, Sanko shiryō”, p.17.

Notes: Figures in brackets correspond to the fourth high-cost medical benefit within 12 months. All monetary values are reported according to the reform in October 2008. The thresholds for residence tax exemptions vary in each municipality.

It should be noted that the thresholds for the lowest income categories (those exempt from paying resident taxes) are set at the municipality level. Therefore, the thresholds between the affluent (e.g., Tokyo metropolitan area) and the unprosperous municipalities (e.g., towns in Hokkaido prefecture) may differ up to 2 times. Overall, the safety net and the 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 health care expenditure (See a review in Appendix C). Overall, the income effect is rarely analyzed with respect to income group. Even when income groups are introduced (e.g., Bessho and Ohkusa, 2006; Tokuda et al., 2009), threshold values for low and middle-income groups are arbitrary chosen.<sup>9</sup> We believe that employing income percentiles (Ishii, 2011; OECD, 2009) may be a better approach for a sample encompassing many unknown municipalities with different levels of poverty lines.

### 3. Empirical models

Following Gravelle et al. (2006), we assume that individual's welfare function  $w(\cdot)$  may be presented as  $w_i = w(y_i, \mathbf{x}_i, c_i)$ , where  $i$  is the index for consumer,  $y_i$  is the utilization of health care,  $\mathbf{x}_i$  are consumer characteristics, and  $c_i$  is access cost. Then, the reduced form equation for health care utilization becomes  $y_i = f(\mathbf{x}_{1i}, \mathbf{x}_{2i}, \mathbf{s}_i)$ , with  $\mathbf{x}_{1i}$  denoting *need* variables (i.e., covariates that should have significant estimated coefficients),<sup>10</sup>  $\mathbf{x}_{2i}$  standing for *non-need* variables (i.e., covariates that should *not* have an effect on health care utilization),<sup>11</sup> and  $\mathbf{s}_i$  indicating supply variables (e.g., per capita number of doctors or number of beds).

Below we outline econometric models for health care access (the binary choice of going to clinic/hospital) and utilization (the amount of health care expenditure). To address income equity in health care access and incurred health care costs (Culyer and Wagstaff, 1993), our empirical analysis focuses on the examination of the estimated coefficients for income groups.

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<sup>9</sup> Bessho and Ohkusa (2006) separate consumers into the following income groups with respect to annual household income: less than 1 mln. Yen, 1-3 mln. Yen, 3-5 mln. Yen, 5-7 mln. Yen, 7-10 mln. Yen, 10-15 mln. Yen, 15-20 mln. Yen, 20-30 mln. Yen, above 30 mln. Yen. At the same time, Tokuda et al. (2009) create categories: less than 1.48 mln. Yen, 1.48 – 4 mln. Yen, 4-6 mln. Yen, above 6 mln. Yen. Note that the annual CPI inflation in the period between the two studies is less than 1%.

<sup>10</sup> E.g., morbidity or self-assessed health.

<sup>11</sup> E.g., income.



### 3.1 Multi-part models

The four-part model distinguishes between non-users of health care, 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

$$\Pr(y_i > 0) = F(y_i, \mathbf{x}_i' \boldsymbol{\beta}_1) \quad (1)$$

$$\Pr(\text{inpatient}_i > 0 \mid y_i > 0) = F(\text{inpatient}_i, \mathbf{x}_i' \boldsymbol{\beta}_2) \quad (2)$$

$$\log(y_i \mid y_i > 0, \text{inpatient}_i = 0) = \mathbf{x}_i' \boldsymbol{\beta}_3 + \varepsilon_i \quad (3)$$

$$\log(y_i \mid \text{inpatient}_i > 0) = \mathbf{x}_i' \boldsymbol{\beta}_4 + v_i \quad (4)$$

$$E\varepsilon_i = E v_i = E(\mathbf{x}_i' \varepsilon_i) = E(\mathbf{x}_i' v_i) = 0, \quad (5)$$

where  $i$  is the index for observations,  $y_i$  denotes health care expenditure,  $\text{inpatient}_i$  indicates inpatient health care expenditure, and  $\mathbf{x}_i$  are covariates. The dependent variables 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 health care expenditure is truncated at zero).

The four-part model (1)-(5) is an extension of the (1)', (3)', (5)' two-part model (Duan et al., 1983; Duan et al., 1984) as specified below:

$$\Pr(y_i > 0) = F(y_i, \mathbf{x}_i' \boldsymbol{\gamma}_1) \quad (1)'$$

$$\log(y_i) = \mathbf{x}_i' \boldsymbol{\gamma}_2 + \xi_i \quad (3)'$$

$$E\xi_i = E(\mathbf{x}_i' \xi_i) = 0, \quad (5)'$$

where  $i$  is the index for observations,  $y_i$  denotes health care expenditure, and  $\mathbf{x}_i$  are covariates.

### 3.2 Generalized linear models

Owing to the retransformation problem in regressions with logged dependent variable (Duan, 1983; Manning, 1998; Mullahy, 1998), estimating linear models (3) and (4) can yield unbiased predictions only when error terms are normal or homoscedastic. More formally, in terms of notations for equation (3), if  $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma_\varepsilon^2 \mathbf{I})$ , then  $E(\mathbf{y}|\mathbf{x}) = \exp(\mathbf{x}' \boldsymbol{\beta}_3 + 0.5 \sigma_\varepsilon^2 \mathbf{I})$ . If  $\varepsilon_i$  are not normal, but i.i.d., then  $E(\mathbf{y}|\mathbf{x}) = \exp(\mathbf{x}' \boldsymbol{\beta}_3) \cdot E(\exp(\boldsymbol{\varepsilon}))$ , and therefore,  $\hat{E}(\mathbf{y}|\mathbf{x}) = \exp(\mathbf{x}' \hat{\boldsymbol{\beta}}_3) \cdot E(\exp(\hat{\boldsymbol{\varepsilon}}))$ . However, the estimate of  $E(\mathbf{y}|\mathbf{x})$  becomes biased in case of heteroscedastic errors. Indeed, when variance is some function  $v(\cdot)$  of

covariates, namely  $\text{Var}(\varepsilon)=v(\mathbf{x})$ , the expression for the expectancy of  $\mathbf{y}$  conditional on  $\mathbf{x}$  becomes  $E(\mathbf{y}|\mathbf{x})=\exp(\mathbf{x}' \boldsymbol{\beta}_3) \cdot v(\mathbf{x})$ .

A solution to the retransformation problem in case of non-normal and heteroskedastic errors is the use of generalized linear models (Nelder and Wedderburn, 1972; McCullagh and Nelder, 1989) for health care expenditure data (Mullahy, 1998; Blough et al., 1999). Although there are other possible solutions,<sup>12</sup> the advantages of generalized linear models are improved precision compared to OLS-methods and robustness of the estimate of the conditional mean (Manning and Mullahy, 2001). Generalized linear models assume a particular form of distribution family, which requires postestimation analysis about the goodness-of-fit.

Generalized linear model specifies the mean and variance functions for  $\mathbf{y}|\mathbf{x}$  by setting a family of distributions  $g(\cdot)$ , as well as the link function  $f(\cdot)$ , so that  $f(E(\mathbf{y}|\mathbf{x})) = \mathbf{x}' \boldsymbol{\beta}$ . We use LIMDEP 9.0 to analyze the models for nonnegative dependent variables with lognormal, gamma, Weibull, and inverse Gaussian families. Let

$$f(E(\mathbf{y}|\mathbf{x}))= \mathbf{x}' \boldsymbol{\beta} \tag{6}$$

$$\mathbf{y}|\mathbf{x} \sim g(\mathbf{y}, \mathbf{x}' \boldsymbol{\beta}, \boldsymbol{\theta}), \tag{7}$$

where  $f(\cdot)$  denotes a logarithmic link function,  $g(\cdot)$  is a family of distribution,  $\mathbf{x}$  are covariates, and  $\boldsymbol{\theta}$  are ancillary parameters.

For each distribution family we examine the model fit, employing normality test of Anscombe residuals (McCullagh and Nelder, 1989; Dobson, 2002; Agresti, 2007) and standardized deviance residuals (Davison and Gigli, 1989).<sup>13</sup> The comparison of the goodness-of-fit between OLS and generalized linear models is conducted with the analysis of residuals (raw bias and mean squared error).

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<sup>12</sup> 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-parametric approaches and extensions of generalized linear models (Basu and Manning, 2009). Recent reviews of the applied literature with generalized linear models and other methods for modeling health care expenditure may be found in Mihaylova et al. (2011), Mullahy (2009), Basu and Mullahy (2009), Buntin and Zaslavsky (2004).

<sup>13</sup> See derivation of model deviance and deviance residuals in the Appendix.

### 3.3 Latent class analysis

#### 3.3.1 Binary choice model with latent classes

The latent class approach (Deb and Trivedi, 1997; Deb and Holmes, 2000) divides consumers into unobservable classes of “high” and “low” users of health care to account for immeasurable consumer characteristics, not captured by self-assessed health and other variables. The binary choice model (1) is extended to a latent class model in the following way:

$$\Pr(y_i > 0) = F(y_i, \mathbf{x}_i' \boldsymbol{\beta}_{1j}), \quad (8)$$

where  $i$  is the index for observations,  $j$  is the index for latent class ( $j = 1 \dots J$ ),  $y_i$  is health care expenditure,  $\mathbf{x}_i$  are covariates related to the demand for health care,  $\boldsymbol{\beta}_{1j}$  are coefficients for  $j$ -th latent class.

The estimations are conducted in LIMDEP 9.0, which determines the most probable latent class by comparing posterior joint probabilities  $\Pr(j|i)$  for all  $j$ -s, with the prior probability  $F_j$  of belonging to latent class  $j$  and posterior joint probability  $\Pr(j|i)$  of belonging to latent class  $j$  calculated as:

$$F_j = \frac{\exp \vartheta_j}{\sum_{j=1}^{J-1} (1 + \exp \vartheta_j)} \quad (9)$$

$$\Pr(j|i) = \frac{F_j \cdot \Pr(i | j)}{\sum_{j=1}^J F_j \cdot \Pr(i | j)}, \quad (10)$$

where  $\Pr(i|j)$  is the density function of  $y_i$  given observation belongs to class  $j$ . Equations (2)-(4) are transformed into a latent class model in a similar way.

#### 3.3.2 Generalized linear models with latent classes

For generalized linear models that fit the data, equations (6)-(7) are extended as follows:

$$f(E(\mathbf{y}|\mathbf{x})) = \mathbf{x}' \boldsymbol{\beta}_j \quad (11)$$

$$\mathbf{y}|\mathbf{x} \sim g(\mathbf{y}, \mathbf{x}' \boldsymbol{\beta}_j, \boldsymbol{\theta}_j), \quad (12)$$

where  $f(\cdot)$  denotes a logarithmic link function,  $g(\cdot)$  is a family of distribution,  $\mathbf{x}$  are covariates,  $j$  is the index for latent class ( $j = 1 \dots J$ ),  $\mathbf{y}$  is health care expenditure,  $\boldsymbol{\beta}_j$  are coefficients,  $\boldsymbol{\theta}_j$  are ancillary parameters. The prior and posterior class probabilities are calculated according to (9) and (10).

### 3.3.3 Specification tests

Greene (2007) proposes the following statistics to test between  $H_0$ : “a latent class (unrestricted) model” and  $H_a$ : “a model without latent classes (restricted model)”:

$$L = 2 (\ln L_u - \ln L_R) \sim \chi^2((J - 1) \cdot (k + 1)), \quad (13)$$

where  $\ln L_u$  is loglikelihood of the unrestricted model,  $\ln L_R$  is loglikelihood of the restricted model,  $J$  is the number of latent classes, and  $k$  is the number of covariates.

Although the statistics  $L$  corresponds to the general logics of likelihood ratio test for nested models, Greene (2007) argues that the validity of the statistics needs to be further investigated, and the use of conventional information criteria is more preferable in the applied analysis.<sup>14</sup> Therefore, to choose between the models with and without latent classes, we use both Greene’s (2007) LR test as specified in (13) and information criteria (AIC and BIC).

## 4. Data

The paper uses the data of Japan Household Panel Survey. 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. There are a number of unique features of this longitudinal survey for the purposes of the analysis of health care demand. First, health care utilization is reported at the individual level.<sup>15</sup> Second, health care utilization is divided into health care in outpatient and inpatient facilities. Finally, health care expenditure is subdivided into the expenditure covered and uncovered by health insurance.

The participation in our analysis is modeled through dichotomous variables “healthcare” for using any health care facility (corresponds to eq.1 in 3.1), and “inpatient care” for seeking care in an inpatient facility given consumer used some health care facility (eq.3 in 3.1). The intensity variable “expenditure” is out-of-pocket payments for health care covered by health insurance (eq. 3 and 4 in 3.1).

We construct dichotomous variables “group 1” through “group 5” for quintiles of the annual disposable (after-tax) household income (with the upper quintile – “group 5” – treated as a reference category). Five interaction terms (income group\*log of annual

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<sup>14</sup>Greene (2007) “Testing for the Latent Class Model”. In: LIMDEP. Version 9.0. Econometric modeling guide. Vol.1. E17.10.5.

<sup>15</sup> While in Japanese Panel Survey of Consumers and Keio Household Panel Survey health care expenditure is reported at the household level.

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, 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, smoking, sports, and checkups reflect health-related life styles. The binary variables for designated city and other cities capture health care supply which is generally better in Japanese urban areas (rural areas, i.e., towns and villages become a reference category). We add a dummy for National Health Insurance, since sometimes there are additional high-cost medical benefits for the poor in this health insurance plan.

We use a subsample of non-elderly consumers (aged below 70), since Japanese elderly have lower nominal coinsurance rates<sup>16</sup> and special thresholds for high-cost medical benefits (Table 2).

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<sup>16</sup> Since 2007 nominal coinsurance rate is 10% for aged above 75 and 20% for aged 70-74.

**Table 2. Descriptive statistics of our sample**

| Variable        | Definition   | Obs  | Mean  | St.Dev. | Min   | Max    |
|-----------------|--|------|-------|---------|-------|--------|
| healthcare      | = 1 if out-of-pocket expenditure for health care covered by health insurance is nonnegative in 2008; 0 otherwise   | 3563 | 0.61  | 0.49    | 0.00  | 1.00   |
| inpatient care  | = 1 if out-of-pocket expenditure for inpatient care covered by health insurance is nonnegative in 2008 given intensity equals 1; 0 otherwise   | 3563 | 0.05  | 0.22    | 0.00  | 1.00   |
| expenditure     | out-of-pocket expenditure for health care covered by health insurance in 2008, thousand yen  | 3563 | 41    | 117     | 0     | 2400   |
| income          | disposable household income in 2008, thousand yen  | 2919 | 5212  | 3822    | 0     | 120000 |
| age             | years of age as of January 31, 2009  | 3563 | 46.64 | 14.41   | 19.84 | 69.99  |
| gender          | =1 if female; 0 if male  | 3563 | 0.51  | 0.50    | 0.00  | 1.00   |
| education       | = 1 if completed junior college, college or university   | 3563 | 0.41  | 0.49    | 0.00  | 1.00   |
| work            | = 1 if was employed last month   | 3555 | 0.74  | 0.44    | 0.00  | 1.00   |
| designated city | = 1 if lives in a designated city, 0 otherwise   | 3563 | 0.26  | 0.44    | 0.00  | 1.00   |
| city            | = 1 if live in a non-designated city, 0 otherwise  | 3563 | 0.64  | 0.48    | 0.00  | 1.00   |
| 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”  | 3555 | 0.09  | 0.29    | 0.00  | 1.00   |
| PDI             | physiological distress index, calculated as the sum of responses to the questions on the recent presence of the below twelve conditions (each response is given on a four-point scale, where “one” refers to “often”, “two” means “sometimes”, “three” implies “almost never”, and “four” stands for “never”):<br><i>headache or dizziness; palpitation or shortness of breath; sensitive stomach and intestines; backache or shoulder pain; get tired easily; catch a cold easily often feel irritated; trouble getting to sleep; feel reluctant to meet people; less concentration on work; dissatisfied with present life; anxiety over the future.</i> | 3401 | 34.24 | 7.15    | 13.00 | 48.00  |
| BMI             | body mass index = $10000 \cdot \frac{\text{weight}(kg)}{\text{height}^2(cm)}$  | 3379 | 22.57 | 3.42    | 14.69 | 75.31  |
| smoking         | = 1 if currently smokes; 0 otherwise   | 3546 | 0.29  | 0.45    | 0.00  | 1.00   |
| drinking        | = 1 if drinks moderately or heavily; 0 otherwise   | 3527 | 0.62  | 0.49    | 0.00  | 1.00   |
| NHI             | = 1 if National Health Insurance; 0 otherwise (other health insurance plan)  | 3563 | 0.29  | 0.46    | 0.00  | 1.00   |
| checkup         | = 1 if had nonnegative expenditure for various checkups in 2008 (apart from checkups at work); 0 otherwise   | 3466 | 0.37  | 0.48    | 0.00  | 1.00   |
| gym             | = 1 if had nonnegative expenditure for doing sports, going to gym, and buying supplements in 2008; 0 otherwise   | 3403 | 0.34  | 0.47    | 0.00  | 1.00   |

## 5. Empirical results

### 5.1 Binary choice model for health care utilization

According to the results of the test for normality of errors (Greene, 2007),<sup>17</sup> we use probit model for binary choice equations of the four-part model (eq.1 and eq.2). For each equation we estimate a model with two latent classes. The prior probabilities for latent class membership are significant and Greene's (2007) likelihood ratio test rejects the null hypothesis of the model without latent classes. Yet, in each case we could not conclude that consumers separate into two latent classes with respect to their binary choice of seeking health care.<sup>18</sup> Indeed, AIC and BIC for the models with and without latent classes are close. Moreover, marginal effects for most of explanatory variables in each latent class are insignificant.

Consequently, for each equation we estimate probit model without latent classes (Table 3). The results reveal that with the exception of the fourth income quintile in eq.1, the coefficients for marginal effects for income groups are insignificant in both eq.1 and eq.2. Moreover, most of other non-need variables are insignificant. Age is the only significant determinant of the binary choice for seeking inpatient care. In case of any type of health care, the significant covariates are age, gender, graduate education, and some lifestyle variables: body mass index and the binary variable for checkups.

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<sup>17</sup> Greene (2007). "A Test for Normality in the Probit Model" In: LIMDEP 9.0. Econometric modeling guide. Vol.1. E18.60.

<sup>18</sup> The result is similar to the previous finding with the 2000-2007 data on Japanese women, where consumers did not separate into latent classes in the binary choice model for seeking health care (Bestremyannaya, 2011).

**Table 3. Marginal effects in the binary choice equations (1) and (2) of a four-part model**

|                      | (1)        |               | (2)            |              |
|----------------------|------------|---------------|----------------|--------------|
|                      | Healthcare |               | Inpatient care |              |
| constant             | 0.2847     | (0.5306)      | -0.3458        | (0.2046)*    |
| age                  | 0.0052     | (0.0006) ***  | 0.0012         | (0.0003) *** |
| group 1 * ln(income) | -0.0026    | (0.0356)      | -0.0149        | (0.0136)     |
| group 2 * ln(income) | 0.0652     | (0.1570)      | 0.0256         | (0.0664)     |
| group 3 * ln(income) | 0.2769     | (0.2840)      | -0.0095        | (0.1187)     |
| group 4 * ln(income) | -0.5591    | (0.2032) ***  | 0.0814         | (0.0859)     |
| group 5 * ln(income) | -0.0429    | (0.0579)      | 0.0179         | (0.0223)     |
| PDI                  | 0.00002    | (0.00004)     | -0.00002       | (0.00001)    |
| BMI                  | 0.0002     | (0.00004) *** | 0.00003        | (0.00002)    |
| gender               | 0.0601     | (0.0169) ***  | -0.0069        | (0.0071)     |
| education            | 0.0901     | (0.0177) ***  | -0.0039        | (0.0076)     |
| lowhcond             | -0.0001    | (0.0002)      | -0.00004       | (0.0001)     |
| smoking              | -0.00001   | (0.0001)      | -0.00004       | (0.00004)    |
| drinking             | -0.00001   | (0.0001)      | 0.00003        | (0.00004)    |
| NHI                  | 0.0051     | (0.0193)      | -0.0018        | (0.0079)     |
| checkup              | 0.0002     | (0.0001) ***  | 0.00002        | (0.00002)    |
| gym                  | -0.00005   | (0.00005)     | -0.00002       | (0.00002)    |
| work                 | -0.00005   | (0.0002)      | -0.00003       | (0.0001)     |
| designated city      | -0.0279    | (0.0316)      | -0.0187        | (0.0100)     |
| city                 | -0.0328    | (0.0283)      | -0.0321        | (0.0122)     |
| group 1              | -0.4811    | (0.5828)      | 0.2701         | (0.2248)     |
| group 2              | -0.9751    | (1.2665)      | -0.0529        | (0.5395)     |
| group 3              | -2.7679    | (2.1023)      | 0.2354         | (0.8946)     |
| group 4              | 4.4861     | (1.6576) ***  | -0.5533        | (0.7128)     |
| Log likelihood       | -2277.81   |               | -697.60        |              |
| Observations         | 2538       |               | 2538           |              |

Notes: \*\*\* p < 0.01, \*\* p < 0.05, \*p < 0.1. Robust standard errors in parentheses. Marginal effects are evaluated at sample means. Group 1, group2, group 3, group 4 and group 5 denote dichotomous variables for log(income) quintiles, with group 1 standing for the lowest quintile, and group 5 indicating the highest quintile.

## 5.2 Modeling health care expenditure with logged dependent variable

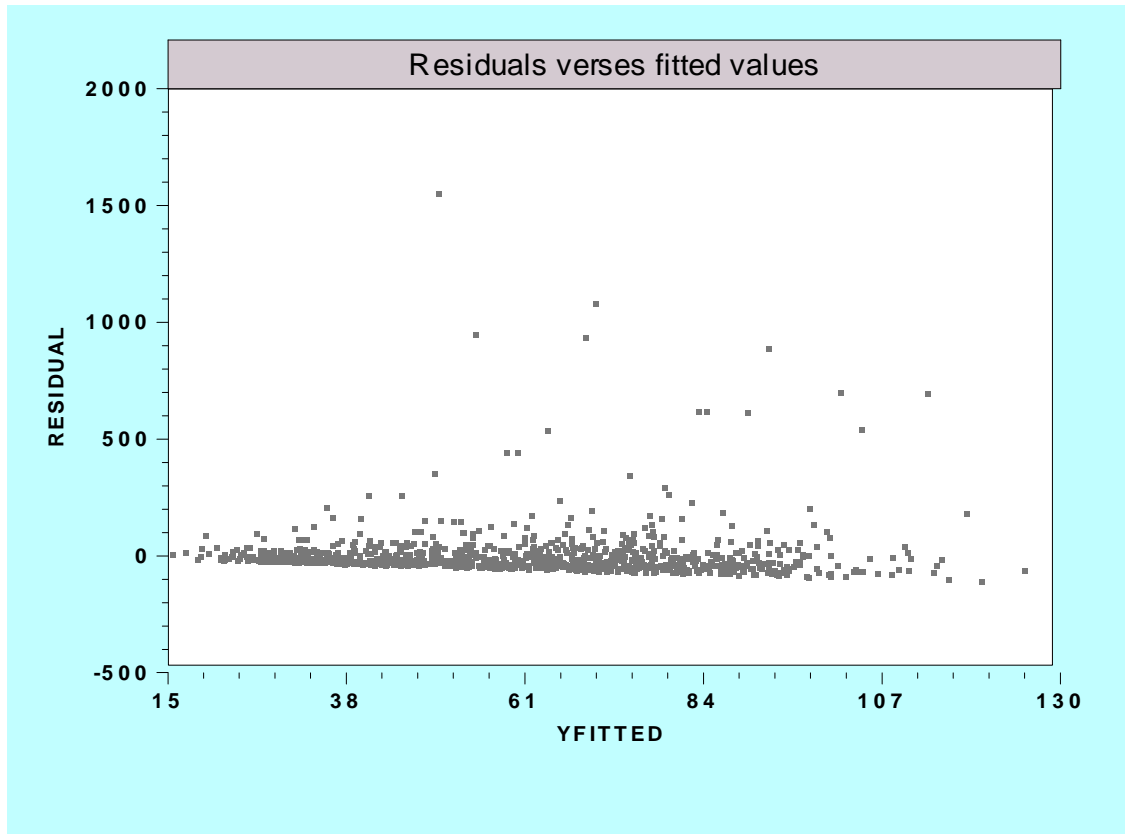
The post-estimation analysis with an ordinary least squares model for equation (3) reveals that the errors are non-normal and heteroscedastic. Consequently, we experiment with generalized linear models with four distribution families: lognormal, gamma, Weibull, and inverse Gaussian. The results of the residual analysis indicate that inverse Gaussian distribution provides the best model fit in terms of the bias, mean squared error, and Anscombe residuals (Table 4, Fig.2-3).



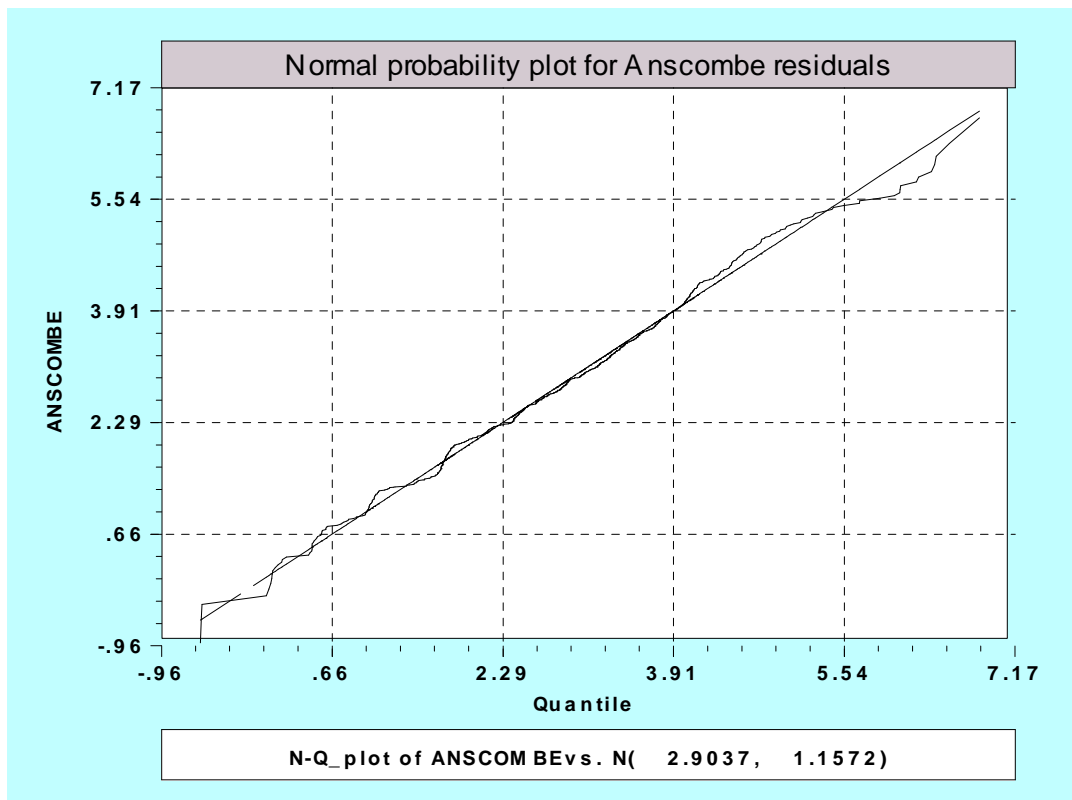
**Table 4. Model comparison**

|                                       | Linear Model<br>(a) | Generalized<br>(b)        | linear<br>(c)         | linear<br>(d)           | models<br>(e)                    |
|---------------------------------------|---------------------|---------------------------|-----------------------|-------------------------|----------------------------------|
|                                       |                     | lognormal<br>distribution | gamma<br>distribution | Weibull<br>distribution | inverse Gaussian<br>distribution |
| Mean raw bias (residual)              | -2.48               | -2.48                     | 60.58                 | -38.39                  | 1.49                             |
| Mean squared error                    | 48.06               | 48.06                     | 15.17                 | 13.42                   | 11.13                            |
| Normality test,<br>Anscombe residuals |                     | 0.00                      | 0.00                  | 0.00                    | 0.57                             |

Notes: In linear model the fitted values are calculated with the smearing factor. Since the general form of Weibull family does not lead to convergence, we use Rayleigh distribution (i.e., the scale parameter in Weibull distribution equals two). Normality test reports the p-value for joint probability in skewness/kurtosis test with the null hypothesis of the standard normal distribution. As for standardized deviance residuals, standardized residuals, and Person residuals, the null hypothesis of normality is not accepted in all the generalized linear models. Dichotomous variables for income groups are excluded from the list of covariates in generalized linear models since they influenced convergence (namely, the marginal effects for these variables were huge). Although the distribution of standardized deviance residuals is close to normal (See Fig.4 in Appendix A), the skewness/kurtosis test rejected the null hypothesis of normality.



**Figure 2.**  
**Residuals verses fitted values for the generalized linear model with inverse Gaussian distribution**



**Figure 3.**

**Quintiles of Anscombe residuals verses quintiles of normal distribution for the generalized linear model with inverse Gaussian distribution**

### 5.3 Income equity in a model with latent classes

#### 5.3.1 Consumers who used only outpatient care

We estimate a generalized linear model with inverse Gaussian distribution and two latent classes, and find that the coefficients for latent class probabilities are significant (Table 5). According to the results of Greene's (2007) LR test for nested models,  $H_0$  of unrestricted model (with latent classes) is not rejected. Similarly, the comparison of information criteria demonstrates that the model with latent classes is preferred to the model without latent classes. Consequently, we may conclude that consumers separate into two latent classes with respect to their outpatient expenditure.

The first latent class (183 observations) is relatively young adults: mean age 44.06, standard deviation 12.46. Only 5% of them have low health condition. The average annual outpatient health care expenditure of the first latent class is 61,377 yen, however, the standard deviation of this variable is high: 197,163 yen. The second latent class contains 857 observations for relatively older adults: mean age 50.98, standard deviation 13.64. The prevalence of low health condition in the second latent class is 15.5%. The average annual outpatient health care expenditure of the second latent class is 60,435 yen, which is close to the value of this variable in the first latent class.

However, the standard deviation of the variable in the second latent class is 2 times smaller than in the first latent class: 80,301 yen.

The coefficients for income groups are insignificant in each of the latent classes. This implies that similarly to our findings for the binary choice models, there is horizontal equity in income in each of the latent classes. The need variables (age and low health condition) are significant covariates in each latent class.

The findings on horizontal equity in Japan may be contrasted to the estimations of log health care expenditure of the US elderly in a linear model with two latent classes, where the coefficients for the lowest income quartile are significant in each class (Deb and Trivedi, 2011).

**Table 5. Estimating health care expenditure with a generalized linear model with inverse Gaussian distribution and latent classes (consumers who used only outpatient care)**

|  | Whole sample        | Latent class 1      | Latent class 2      |
|--|---------------------|---------------------|---------------------|
| constant                               | -0.9202 (0.2689)*** | 3.8837 (2.3896)     | -0.7179 (0.8433)    |
| age                                    | -0.0269 (0.0037)*** | -0.0493 (0.0083)*** | -0.0244 (0.0040)*** |
| group 1 * ln(income)                   | 0.0249 (0.0157)     | -0.3648 (0.2880)    | -0.0126 (0.1057)    |
| group 2 * ln(income)                   | -0.0060 (0.0095)    | -0.2962 (0.2532)    | -0.0412 (0.0959)    |
| group 3 * ln(income)                   | 0.0079 (0.0143)     | -0.2347 (0.2520)    | -0.0315 (0.0935)    |
| group 4 * ln(income)                   | -0.0062 (0.0118)    | -0.2379 (0.2381)    | -0.0446 (0.0900)    |
| group 5 * ln(income)                   | -0.0204 (0.0103)**  | -0.3210 (0.2239)    | -0.0215 (0.0858)    |
| PDI                                    | 0.0005 (0.0003)     | -0.0200 (0.0120)*   | -0.0066 (0.0060)    |
| BMI                                    | 0.0001 (0.0005)     | -0.0121 (0.0292)    | -0.0069 (0.0113)    |
| gender                                 | -0.1475 (0.0932)    | -0.2096 (0.2168)    | 0.2295 (0.0937)**   |
| education                              | -0.1852 (0.1045)*   | -0.3255 (0.2189)    | -0.0767 (0.0938)    |
| lowhcond                               | -0.0027 (0.0285)    | -1.4520 (0.5503)*** | -0.4783 (0.1374)*** |
| smoking                                | 0.0011 (0.0115)     | 0.2859 (0.2579)     | 0.1836 (0.0952)*    |
| drinking                               | -0.0009 (0.0009)    | 0.3505 (0.2373)     | 0.0955 (0.0882)     |
| NHI                                    | 0.0291 (0.1240)     | 0.0003 (0.2952)     | 0.1038 (0.0953)     |
| checkup                                | 0.0005 (0.0006)     | -1.8385 (0.2932)*** | 0.3071 (0.1093)***  |
| gym                                    | 0.0005 (0.0005)     | 0.3348 (0.1982)     | -0.2290 (0.0877)*** |
| work                                   | -0.0001 (0.0112)    | -0.3572 (0.2662)    | 0.3887 (0.1140)***  |
| designated city                        | 0.0975 (0.1876)     | 0.6591 (0.4855)     | 0.2396 (0.1646)     |
| city                                   | -0.0763 (0.1768)    | 0.9931 (0.4660)**   | 0.1640 (0.1595)     |
| Log likelihood                         | -6871.34            | -5089.93            | -5089.93            |
| Observations                           | 1040                | 183                 | 857                 |
| Scale parameter in the distribution    | 4.8499              | 4.0426 (0.1978)***  | 8.0837 (0.3952)***  |
| Prior probability for class membership |                     | 0.2968 (0.0359)***  | 0.7032 (0.0359)***  |

Notes: The dependent variable is annual health care expenditure. The Table reports coefficients for covariates in conditional mean function, and robust standard errors in parentheses.

\*\*\* p< 0.01, \*\* p< 0.05, \*p< 0.1.

### 5.3.2 Consumers who used inpatient care

The results of the heteroscedasticity test indicate that the errors in the ordinary least squares models for health care expenditure of consumers who used inpatient care (eq.4) are homoscedastic. Consequently, we do not use generalized liner models and employ an OLS model with latent classes. Since the subsample of inpatient care users is 141 consumers, we keep the minimal number of covariates. Namely, the regressors are age, gender, the binary variable for low health condition, and the dummies for income quintiles. The results of the estimations reveal insignificance of income groups in each latent class (Table 6). In other words, horizontal equity is found for health care expenditure of Japanese consumers who used inpatient care.

**Table 6. Estimating a latent class linear model for consumers who used inpatient health care**

|  | <b>Whole sample</b>    | <b>Latent class 1</b>   | <b>Latent class 2</b> |
|--|------------------------|-------------------------|-----------------------|
| constant                               | 319.4091 (103.4628)*** | 2112.9158 (735.3916)*** | 24.4264 (52.2672)     |
| age                                    | -1.7126 (1.8454)       | -27.3837 (10.1811)***   | 1.9350 (0.8366)**     |
| gender                                 | -1.0436 (52.1148)      | -303.7585 (378.7529)    | 19.2329 (21.5324)     |
| group 1                                | 7.3974 (51.8004)       | 347.6722 (507.6971)     | -20.3974 (25.9890)    |
| group 2                                | 11.3969 (52.1259)      | -280.3299 (478.7233)    | -5.9836 (32.4999)     |
| group 3                                | -61.4197 (57.7608)     | -281.7384 (1505.5319)   | 0.4613 (38.3753)      |
| group 4                                | 42.6317 (57.4747)      | 476.0366 (608.9722)     | 33.6805 (26.9913)     |
| lowhcond                               | 0.0761 (0.3284)        | 432.8034 (336.8508)     | 42.8828 (24.9714)*    |
| Log likelihood                         | -1182.58               | -912.14                 | -912.14               |
| Observations                           | 141                    | 19                      | 122                   |
| Prior probability for class membership |                        | 0.1568 (0.0439)***      | 0.8432 (0.0439)***    |

Note: The dependent variable is logarithm of annual health care expenditure for the subsample that used inpatient care. The Table reports coefficients for covariates and robust standard errors in parentheses. \*\*\* p< 0.01, \*\* p< 0.05, \*p< 0.1.

## 6. Discussion

Our estimations, which account for unobservable consumer heterogeneity through a latent class approach, reveal horizontal equity in health care access and the amount of out-of-pocket expenditure for health care covered by Japanese social health insurance. Overall, the presence of horizontal equity in health care access and utilization in Japan is similar to the findings on equitable or pro-poor non-specialist care utilization in OECD countries (van Doorslaer et al., 2004). Moreover, in terms of total health care expenditure of consumers, social health insurance system in Japan is found to be more equitable than in Germany (Ikegami et al., 2011).

However, there are other aspects where Japanese social health insurance system demonstrates income inequity: health insurance premiums and catastrophic coverage (Ikegami et al., 2011; Hashimoto et al., 2011; HGPI, 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 (Besstremyannaya, 2011). 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 5). The differences in the share of premiums in household income between income quintiles are statistically significant.

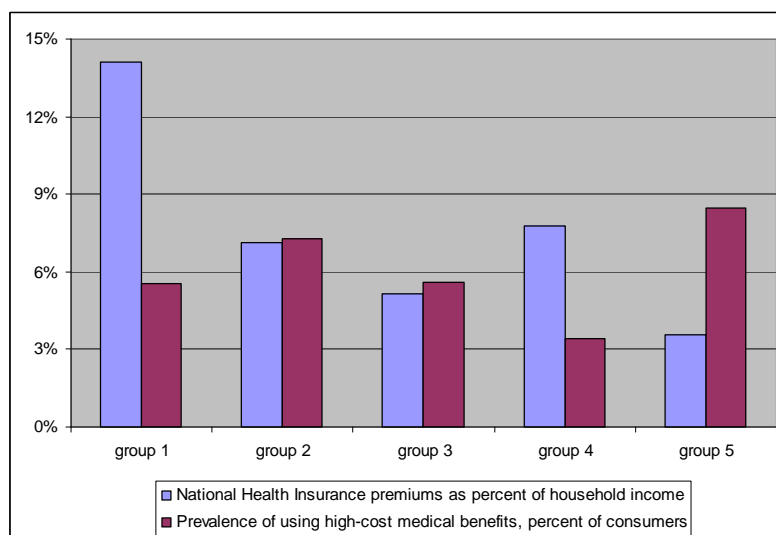
Overall, horizontal inequity in premiums is common in the developed countries with social health insurance (Wagstaff, 2010). Yet, a solution to the problem of intra-health insurance plans and within-NHI plan inequity in premiums in Japan may be found in the consolidation of municipal NHI plans at the prefectural level, which would raise health care 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 (Fig.5). 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 quintile is explained by higher health care 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.<sup>19</sup>

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<sup>19</sup> Overall, Japanese consumers have very limited knowledge about the system of high-cost medical benefits: the results of January 2009 survey of 1,016 respondents 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 (HGPI, 2009).



**Figure 5. Share of premium in household income and prevalence of applying for catastrophic coverage by income quintile (non-elderly consumers).**

Source: Author's estimations according to JHPS, 2009.

Note: The share of premium in household income could be estimated only for single respondents in National Health Insurance.

## 7. Conclusion

The paper studies horizontal equity in health care access and utilization in Japan by estimating the coefficients for income groups in 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 and Trivedi, 1997). We address a retransformation problem in the equations with log of health care expenditure as dependent variable, using Greene's (2007) generalized linear models with latent classes.

Our sample is the 2009 data for health care expenditure by 4,022 adult consumers (Japan Household Panel Survey, wave 1). The survey distinguishes between consumer expenditure covered and non-covered by health insurance, which allows the analysis of income equity in Japanese social health insurance system.

The coefficients for income groups are insignificant both in the binary choice models for inpatient/outpatient health care use, and in the models for health care expenditure. Consumers separate into two latent classes in the generalized linear model for outpatient health care expenditure.

Overall, the results of the estimations reveal horizontal equity of health care in Japan. However, horizontal inequity may be found in health insurance premiums and catastrophic health care coverage.

## Appendix

### A. Derivation of model deviance and deviance residuals

According to the definitions in Nelder and Wedderburn (1972) and McCullagh and Nelder (1989), the model deviance  $D$  is “twice the difference between the log likelihood achieved under the model and the maximum attainable value”. McCullagh and Nelder (1989) define deviance residuals  $r_D$  as

$$r_D = \text{sign}(y - \mu) \sqrt{d_i},$$

where  $\sum_{i=1}^N d_i = D$ . Here  $i$  is the index of observation, with the total sample size  $N$ .

Nelder and Wedderburn (1972) use an example of gamma distribution to demonstrate an approach for calculating model deviance. Below we adopt the approach to derive model deviance and deviance residuals for lognormal, Rayleigh, and inverse Gaussian distributions.

#### *Lognormal distribution*

Loglikelihood function  $\ln L_i$  for lognormal distribution takes the form (Greene, 2007)

$$\ln L_i = -\frac{1}{2} \cdot \left\{ \ln \theta^2 + \ln(2\pi) + \frac{1}{\theta^2} \left[ \ln y_i - \ln(\beta' x_i) + \frac{\theta^2}{2} \right]^2 \right\}, \quad (\text{A1})$$

where  $\theta = \ln(1 + \sigma^2)$ . Rewriting (A1) in terms of  $\mu_i = E(y_i | x_i) = \beta' x_i$  leads to

$$\ln L_i(\mu_i) = -\frac{1}{2} \cdot \left\{ \ln \theta^2 + \ln(2\pi) + \frac{1}{\theta^2} \left[ \ln y_i - \ln(\mu_i) + \frac{\theta^2}{2} \right]^2 \right\}. \quad (\text{A2})$$

Since only  $i$ -th component of the sum  $\ln L$  depends on  $\mu_i$ , solving maximization problem

$$\ln L = \sum_{i=1}^N \ln L_i(\mu_i) \rightarrow \max_{\mu_i} \quad (\text{A3})$$

is equivalent to finding solutions to  $N$  maximization problems  $\ln L_i(\mu_i) \rightarrow \max_{\mu_i}$  (A4)

Differentiating (A2) with respect  $\mu_i$  yields the first-order conditions

$$\ln y_i - \ln(\mu_i) + \frac{\theta^2}{2} = 0, \quad (\text{A5})$$

$$\text{with the solution } \mu_i^* = y_i \cdot \exp\left\{\frac{\theta^2}{2}\right\}. \quad (\text{A6})$$

$$\text{Consequently, } \ln L_i(\mu_i^*) = -\frac{1}{2} \cdot \left\{ \ln \theta^2 + \ln(2\pi) \right\}. \quad (\text{A7})$$

By definition,  $d_i = 2 \cdot (\ln L_i(\mu_i^*) - \ln L_i(\hat{\mu}_i))$ . (A8)

Writing (A7) for  $\ln L_i(\mu_i^*)$  in (A8) and plugging in  $\hat{\mu}_i$  in (A2) to get  $\ln L_i(\hat{\mu}_i)$ , we rewrite (A6) as

$$d_i = \left( \frac{\ln y_i - \ln \hat{\mu}_i}{\theta} + \frac{\theta}{2} \right)^2. \quad (\text{A9})$$

Finally,  $r_{Di} = \text{sign}(y_i - \hat{\mu}_i) \cdot \left( \frac{\ln y_i - \ln \hat{\mu}_i}{\theta} + \frac{\theta}{2} \right)$ . (A10)

### Rayleigh distribution

The piecewise loglikelihood function  $\ln L$  is the sum of the elements  $\ln L_i(\mu_i)$ , where  $\mu_i = E(y_i|x_i)$ . Each term  $\ln L_i(\mu_i)$  takes the form:

$$\ln L_i(\mu_i) = \ln \frac{\pi}{2} - 2 \ln \mu_i + \ln y_i - \frac{\pi y_i^2}{4 \mu_i^2} \quad (\text{A11})$$

The maximization of  $\ln L$  is equivalent to solving the following maximization problems for each  $\ln L_i(\mu_i)$ :

$$\ln L_i(\mu_i) \rightarrow \max_{\mu_i} \quad (\text{A12})$$

Differentiating (A11) with respect to  $\mu_i$ , we obtain first order conditions

$$-\frac{2}{\mu_i} - \frac{\pi y_i^2}{4 \mu_i^3} \cdot (-2) = 0 \quad (\text{A13})$$

Therefore,  $\mu_i^* = \frac{\sqrt{\pi}}{2} \cdot y_i$  (A14)

Plugging in  $\mu_i^*$  in (A11) yields:

$$\ln L_i(\mu_i^*) = \ln \frac{\pi}{2} - 2 \ln \left( \frac{\sqrt{\pi}}{2} \cdot y_i \right) + \ln y_i - 1 \quad (\text{A15})$$

By definition,  $d_i = 2 \cdot (\ln L_i(\mu_i^*) - \ln L_i(\hat{\mu}_i))$ . (A16)

Plugging in  $\hat{\mu}_i$  in (A11) we obtain  $\ln L_i(\hat{\mu}_i)$ , and then rewrite (A16) as

$$d_i = 4 \ln \left( \frac{\hat{\mu}_i}{\frac{\sqrt{\pi}}{2} \cdot y_i} \right) - 2 + \frac{\pi}{4} \cdot \left( \frac{y_i}{\hat{\mu}_i} \right)^2 \quad (\text{A17})$$



$$\text{Finally, } r_{Di} = \text{sign}(y_i - \hat{\mu}_i) \cdot \sqrt{4 \ln \left( \frac{\hat{\mu}_i}{\frac{\sqrt{\pi}}{2} \cdot y_i} \right) - 2 + \frac{\pi}{4} \cdot \left( \frac{y_i}{\hat{\mu}_i} \right)^2}. \quad (\text{A18})$$

### *Inverse Gaussian distribution*

The piecewise loglikelihood function  $\ln L$  is the sum of the elements  $\ln L_i(\mu_i)$ , where  $\mu_i = E(y_i|x_i)$ . Each term  $\ln L_i(\mu_i)$  takes the form:

$$\ln L_i(\mu_i) = \ln p - \frac{1}{2} \cdot \ln(2\pi) - \frac{3}{2} \cdot \ln y_i - \frac{1}{2} \cdot \frac{\left( \frac{py_i}{\mu_i} - p \right)^2}{y_i}, \quad (\text{A19})$$

where  $p$  is the scale parameter of inverse Gaussian distribution.

The maximization of  $\ln L$  is equivalent to solving below maximization problems for each  $\ln L_i(\mu_i)$ :

$$\ln L_i(\mu_i) \rightarrow \max_{\mu_i} \quad (\text{A20})$$

Differentiating (A19) with respect to  $\mu_i$ , we obtain first order condition

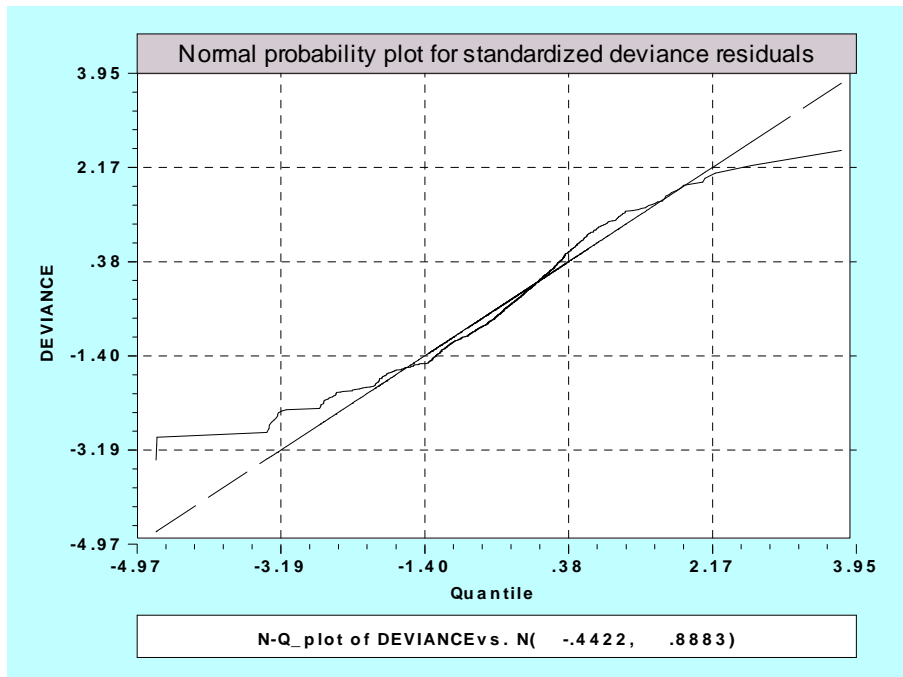
$$\mu_i^* = y_i \quad (\text{A21})$$

Plugging in  $\mu_i^*$  in (A19) we obtain  $\ln L_i(\mu_i^*)$ , and plugging in  $\hat{\mu}_i$  in (A19) to get  $\ln L_i(\hat{\mu}_i)$ . Therefore,

$$d_i = 2 \cdot (\ln L_i(\mu_i^*) - \ln L_i(\hat{\mu}_i)) = \frac{p^2}{y_i} \cdot \left( \frac{y_i}{\hat{\mu}_i} - 1 \right)^2 \quad (\text{A22})$$

$$\text{Finally, } r_{Di} = \text{sign}(y_i - \hat{\mu}_i) \cdot \frac{p}{\sqrt{y_i}} \cdot \left( \frac{y_i}{\hat{\mu}_i} - 1 \right) \quad (\text{A23})$$

In the generalized linear model for outpatient health care expenditure with our data, inverse Gaussian distribution family provides the best goodness of fit in terms of raw bias, mea squared error and Anscombe residual (See Appendix B). The distribution of standardized deviance residuals is close to normal (See Fig.4 below), yet, the skewness/kurtosis test rejected the null hypothesis of normality.



**Figure 4.**

**Quintiles of standardized deviance residuals verses quintiles of normal distribution for the generalized linear model with inverse Gaussian distribution for our sample**

## B. Derivation of Anscombe residuals

In view of Anscombe's (1953) search for residuals which would normalize the distribution of the dependent variable, McCullagh and Nelder (1989) define Anscombe residuals  $r_A$  as:

$$r_{Ai} = \frac{A(y_i) - A(\mu_i)}{A'(\mu_i)\sqrt{V(\mu_i)}} \quad (\text{B1})$$

$$A(\cdot) = \int_{-\infty}^{\cdot} \frac{dt}{V^{1/3}(t)}, \quad (\text{B2})$$

where  $i$  denotes the index for observation,  $y_i$  is the dependent variable,  $\mu_i$  stands for the conditional mean  $E(y_i|\mathbf{x}_i)$ , and  $V(\cdot)$  is variance function for  $\mu_i$ .

This produces  $r_A = \frac{3(y^{1/3} - \mu^{1/3})}{\mu^{1/3}}$  for gamma distribution and  $r_A = \frac{\ln y - \ln \mu}{\mu^{1/2}}$  for inverse Gaussian distribution (McCullagh and Nelder, 1989).

The direct application of (B1)-(B2) reveals that the scale parameters of the distributions are neglected in the formulas for  $V(\cdot)$ . Therefore, our application of (B1)-(B2) for Weibull distribution and lognormal distribution (in both cases  $V(\mu) \propto \mu^2$ )

yields  $r_A = \frac{3(y^{1/3} - \mu^{1/3})}{\mu^{1/3}}$ .

### C. Studies estimating income effect on health care 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, Liu, Lee, Yoshikawa (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 health care 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 health care (a sum of out-of-pocket payment and traveling cost to health care 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   |

| <b>Study</b>             | <b>Demand variable</b>   | <b>Sample</b>   | <b>Income variable</b>                        | <b>Model</b>  | <b>Income effect</b>   |
|--------------------------|--|---|---|---|--|
| Ii and Ohkusa (2002a)    | 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   |
| Bessho and 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)         | 1,249 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. |

| <b>Study</b>         | <b>Demand variable</b>  | <b>Sample</b>  | <b>Income variable</b>                             | <b>Model</b>  | <b>Income effect</b>   |
|----------------------|---|--|--|---|--|
| Tokuda et al. (2009) | Visits to physicians, visits to pharmacy, use of complementary and alternative medicine | 1,406 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 health care 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 |

#### D. Sampling procedure in Japan Household Panel Survey

Japan Household Panel Survey is established in 2009 as a national sample of 4022<sup>20</sup> adults (aged above 20).<sup>21</sup> The first wave of the survey was conducted on January 31, 2009.

Respondent are selected according to a two-stage random sampling procedure. At the first stage, all localities in Japan are divided into 24 groups in the following way: three types of localities<sup>22</sup> (designated cities,<sup>23</sup> other cities, towns and villages<sup>24</sup>) are selected in each of the eight geographic zones<sup>25</sup> (Hokkaido, Tohoku, Kanto, Chubu, Kinki, Chugoku, Shikoku,<sup>26</sup> Kyushu). The sample size for each group is determined according to the share of its population in the National Residents Register (as of March 31, 2008). The survey areas<sup>27</sup> in each group are then randomly selected out of enumeration districts for the 2005 National Census. The preliminary sample at the second stage is 9,633 people. The response rate is 41,5%.

With respect to the way of filling in the questionnaire, localities are randomly divided into 2 types: 1) self-response (*drop-off pick-up* method): questionnaires are distributed to respondents, who fill them in and then submit to the interviewers at their second visit; 2) self-response supplemented by person-to-person interview (*drop-off pick-up* method plus an interview): questionnaires are distributed to respondents, who fill them in and then submit to the interviewers at their second visit; the interviewers also ask respondents questions at the second visit.

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<sup>20</sup> The target sample of 4000 plus the additional back-up sample of 22 respondents.

<sup>21</sup> Our examination of the respondents in wave 1 (2009) demonstrated that 3 persons were 19 at the moment of the survey.

<sup>22</sup> According to the standard administrative division of types of settlements in Japan.

<sup>23</sup> With large population and certain features of prefectural governments.

<sup>24</sup> Chouson

<sup>25</sup> According to the standard geographic division of Japan.

<sup>26</sup> There are no designated cities in Shikoku.

<sup>27</sup> The number of survey areas was chosen to encompass approximately 10 respondents from the target sample.

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