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Abstract

The paper exploits finite mixture (latent class) models to account for consumer heterogeneity in estimating the effect of coinsurance rate on the demand for health care. The parametric analysis employs a two-part model, a Tobit model, and generalized linear models with latent classes. The non-parametric analysis uses matching estimators in each latent class to construct a control group of consumers and measure the average treatment effect of the natural experiment with a rise in nominal coinsurance rate. The paper exploits the 2000-2008 data of the Japanese Panel Survey of Consumers and the 2008 data of Japan Household Panel Survey. The estimations demonstrate a significant negative effect of nominal coinsurance rate on the demand for health care. The effect is primarily noticeable in the latent class of consumers with high health care demand, who constitute 21% of the sample. Our finding with the latent class models with Japanese data, where the assignment of insurance plans is exogenous, is similar to the results with the RAND Health Insurance Experiment data, where the assignment was randomized.

Keywords: health insurance, coinsurance rate, panel data latent class model, average treatment effect, price elasticity, matching estimators

JEL codes: I10, I18, G22, R22

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1 Introduction

Originally believed to be a means of dealing with moral hazard, coinsurance rate in fact may be regarded as consumer price for health care. Consequently, coinsurance rate is often employed as an instrument of containing consumer demand for health care. This prompts empirical estimates of the effect in order to evaluate actual or planned reforms in coinsurance rates (Phelps and Newhouse, 1974). Overall, a considerable amount of research generally demonstrates a negative and significant effect of coinsurance rate (Cutler, 2002). However, owing to heterogeneity of individuals, the commonly used multi-part models for health care demand may fail to provide adequate fit in terms of health care expenditure and, therefore, are likely to result in biased estimates of the coefficients for the covariates of health care expenditure (Deb and Trivedi, 2002).

A solution to the problem of raising the accuracy of the estimations is the use of finite mixture models, which assume that individuals belong to a finite number of unobserved latent classes (Hagenaars and McCutcheon, 1995; McCutcheon, 1987; Clogg, 1981). In an application to health economics (Deb and Trivedi, 1997; Deb and Holmes, 2000) the classes approximate the groups of the users with high and low demand for health care (frequent and infrequent users, respectively), and latent class membership is associated with unobservable state of health, not fully captured by self-assessed health and other measurable consumer characteristics. A few papers that employ the latent class approach in assessing various price effects on the demand for health care (Deb and Trivedi, 2002; Schmitz, 2012; Farbmacher, 2011) demonstrate that the effects are heterogeneous across the classes.

Since endogeneity of observable parameters may become another source of bias in the analysis of the price effect, the literature employs matching estimators (Barros, 2008) that construct the control group of consumers and estimate the average treatment effect of the price changes.

To the best of our knowledge, the paper is the first application of a finite mixture (latent class) model to measuring the effect of coinsurance rate in case of a natural experiment. The methodological novelty of this paper is twofold. Firstly, we fit health care expenditure in the second part of the two-part model using panel data generalized linear models with latent classes. Secondly, we combine latent class analysis and matching estimator approach in measuring the effect of coinsurance rate on the amount of health care expenditure. We analyze the average treatment effect of the April 2003 rise in nominal coinsurance rate on the amount of outpatient health care expenditure in Japan. After measurement of the average treatment effect in the reform year, difference-in-difference estimations are used to estimate the changes in health care expenditure in post-reform years and the pre-reform year. The analysis exploits the 2000-2008 data of Japanese Panel Survey of Consumers (The Institute for Research on Household Economics, Tokyo). The amount of health care expenditure outside health insurance is imputed according to the 2008 data of Japan Household Panel Survey (Keio University Joint Research Center for Panel Studies).

It should be noted that raising coinsurance rates was an important tool of restricting Japanese health care expenditure in 1980s-early 2000s. In fact, health care system in Japan is known to be one of the most effective and cost-efficient among other developed countries (Ikegami, 2005; Imai, 2002). Yet, the country faces a steady growth in health care spending, which started to exceed the rate of GDP growth in 1990s. The increase in health care spending is accompanied by a low growth of health care revenues, owing to aging population and decrease in labor force (Imai, 2002). Therefore, Japan explores various methods of containing health care expenditure, with coinsurance rate being one of the instruments to regulate consumer demand for health care.

The results of our estimations demonstrate a significant negative effect of nominal coinsurance rate on the demand for health care in Japan. Yet, the impact of nominal coinsurance rate is primarily noticeable in the latent class of the frequent users of health care. Our finding with the latent class models with Japanese data, where the assignment of insurance plans is exogenous, is similar to the results with RAND Health Insurance Experiment data (Deb and Trivedi, 2002), where the assignment was randomized. Overall, our results justify the reliance on coinsurance rate as an instrument of cost containment. However, decreasing the price of medical services and drugs in unified fee schedule and enhancing the efficiency of health care providers may offer alternative means to dealing with the burden of health care costs in Japan.

The remainder of the paper is structured as follows. Section 2 outlines various instruments for cost containment and the dynamics of nominal coinsurance rates in different health insurance plans in Japan in 1960s-2000s. Section 3 sets up empirical models for measuring the effect of coinsurance rate on the demand for health care. Section 4 describes the data of Japanese Panel Survey of Consumers. The findings of the empirical estimations are summarized in section 5. Section 6 discusses the results of the analysis with the latent class model, and Section 7 concludes the paper. Details on the sampling procedure in Japanese Panel Survey of Consumers, and the derivation of deviance residuals and Anscombe residuals for measuring goodness-of-fit in generalized linear models are presented in the Appendices.

2 Coinsurance rates in Japanese social health insurance system

Since 1961 Japan has a mandatory and universal social health insurance. The enrolment in one of mutually exclusive health insurance plans is obligatory and depends on enrollee's age and status at the labor market. The following health insurance plans exist in Japan: 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, 3) company-managed insurance associations formed by firms with over 300 employees for employees and their dependents; 4) mutual aid associations' benefit schemes (Table 1).

Table 1. Health insurance plans in Japan

| Name | Eligible enrollees | Share by enrollees | Share by health care expenditure | Comments |
|--|--|--------------------|----------------------------------|---|
| National health insurance | Self-employed, unemployed and their dependents, retirees | 40.3% | 51.8% | The share of enrollees increased from 37.7 of insured in all the schemes in 2000 to 40.3 in 2006 (Japan Statistical Yearbook, 2011). Managed by municipalities |
| Government-managed health insurance | Small firms' employees and their dependents | 28.2% | 23.8% | Managed by the government |
| Company (society, association)-managed health insurance | Insurance societies formed by firms with over 300 employees for employees and their dependents | 23.9% | 18.3% | The number of societies has been gradually decreasing: while in 1999 it equaled almost 2000 (Ikegami and Campbell, 1999), by 2010 it fell to 1,497 (MHLW, 2010). The share of enrollees went down from 25.1% of insured in all the schemes in 2000 to 23.9% in 2006 (Japan Statistical Yearbook, 2011). |
| Mutual aid associations for national government employees' | National government employees' and dependents | 1.9% | 1.4% | 21 associations for national government employees' (MHLW, 2010) |
| Mutual aid associations for local government employees' | Local government employees' and dependents | 4.8% | 4.0% | 55 associations for local government employees' (MHLW, 2010) |
| Mutual aid association for private school teachers | Private school teachers and dependents | 0.7% | 0.6% | 1 association (MHLW, 2010) |
| Seamen's insurance | Seamen and dependents | 0.1% | 0.1% | Managed by the government |

Notes: Columns 3 and 4 present corresponding percentage shares of the plan in the total national figure as of 2006 (according to the data in Japan Statistical Yearbook, 2011). Health insurance plan for people above 70 (insurance for the elderly) is not reported in the Table.

Japanese social health insurance is based on a free access. 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).² Medical services and drugs to be offered within social health insurance and their costs are set by the Ministry of Health, Labor, and Welfare (MHLW) in a biennially revised unified fee schedule.³ Since drug dispensing has traditionally constituted the major share of physicians' income in

² Consumer payments for seeking care without referral in large hospitals (with over 200 beds) or in specialized (high-technology) hospitals are negligible.

³ 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). It should be noted that companies may offer additional services above the MHLW-defined fee schedule. In particular, from 3.1 to 8.4% (on average 6.6%) of contributions to company-managed insurance is spent on check-ups and preventive care, and up to 4.4% (on average 2.9%) goes to additional services, which commonly deal with reimbursement of patients' out-of-pocket payments (Ikegami and Campbell, 1999). Certain companies may have a network of affiliated hospitals. The number of these hospitals, however, has considerably declined: from 267 in 1965 to 59 in 2003 (Ikegami and Campbell, 2004).

Japan,⁴ the cost of an average daily dosage of medicine (i.e. 10 yen) is the unit for calculations. In other words, unified fee schedule points assigned to each procedure and drug are translated into monetary value through multiplication by 10.

Japanese social health insurance is financed by premiums, coinsurance payments, and government subsidies. In fact, Japanese social health insurance system is highly subsidized. The share of central and local government subsidies steadily went up in the analyzed period and accounted for 36.7% of all sources of health care financing in 2007 (Table 2). Since the share of central government subsidies in the sources of financing of the main health insurance plans was decreasing over the same period (Figure 1), the major burden falls on regional governments. Despite the fact that premiums are constantly lifted to raise revenues of the health care system,⁵ the share of premiums in the sources of financing is going down.

Table 2. Sources of financing in Japanese social health insurance system, percent

| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
|---|------|------|------|------|------|------|------|------|------|
| Central and regional government subsidy | 32.3 | 32.6 | 33.2 | 34.1 | 34.8 | 36.4 | 36.6 | 36.7 | 37.1 |
| Premium | 53.4 | 53 | 51.9 | 50.2 | 49.8 | 49.2 | 49 | 49.2 | 48.8 |
| Coinsurance payments | 14.3 | 14.4 | 14.9 | 15.8 | 15.4 | 14.4 | 14.4 | 14.1 | 14.1 |

Sources: Kouseiroudochousa, 2010, 2009, 2008, 2007; MHLW (2007) <http://www.mhlw.go.jp/shingi/2007/02/s0206-5.html>

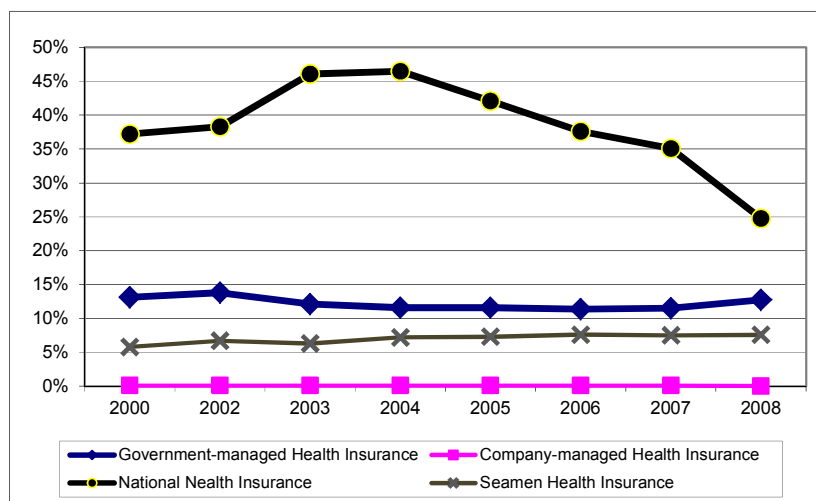


Figure 1. Share of central government subsidy in the revenues of major health insurance plans

Note: 2001 data are unavailable. Sources: Kouseiroudochousa, 2010, 2009, 2008, 2007, 2006; Iryokeizaishisetsuchosa 2003, 2001.

⁴ Until the end of the 19th century the Japanese doctors practicing traditional medicine (Kampo) offered their services for free, asking reimbursement only for the cost of medicines they used for treatment.

⁵ The premium in national health insurance is determined by each municipality. It is based on income, property and size of the insured household. The premium in government-managed health insurance is equally shared between employer and employee. In 2002 the premium was raised from 7.2% of the salary to 8.2%, and in 2010 was further increased to 9.34%. Employer's contributions vary from 50 to 80% of the premium in company-managed health insurance, with the average value of 56.7% (Ikegami, 1996a). Since 2002 the premiums in company-managed insurance are in the range of 5.8 to 9.5% of the salary (Ikegami and Campbell, 1999). The variation of insurance payments is primarily noticed at the inter-industry level: the highest premiums are paid in the industries with high average age of workers, high level of professional morbidity, and low salaries (Campbell and Ikegami, 1998). Since 1977 biannual bonuses are included in the total income, which is used in the calculation of health insurance premium. However, the corresponding premium in case of bonuses becomes lower than in the case of salary. Consequently, while on average the premium in company-managed insurance was 8.2% of the salary in 1991, the share of premium in the actual average monthly income was only 2.7% (Ikegami, 1996a).

In 1990s the average rate of real growth of Japanese total health care expenditure started to exceed the rate of real GDP growth. This implied increasing amount of government's financial support to health care system. Consequently, the country searches for various means to contain health care costs and decrease the burden of public spending. One of the traditionally used instruments for this purpose is containing consumer demand through the size of nominal coinsurance rates.

The nominal coinsurance rate for each plan is determined by the Health Insurance Law. When national health insurance became universal in 1961, nominal coinsurance rate within this plan was established as 50%. It was lowered to 30% for heads of household in 1963 and for dependents in 1968. Similarly, the policy of enhancing health care accessibility led to decrease of coinsurance rate for dependents in company-managed insurance and government-managed insurance from 50% to 30% in October 1973. Copayments did not exist for heads of households in company-managed insurance owing to special social guarantees to "salary men" during the country's growth in 1960s-1970s. Yet, soaring health care costs, and decelerating growth of population and of labor force led to a 10% coinsurance rate, established in 1984 for heads of households in company-managed insurance. Furthermore, in September 1997 all health insurance plans saw an introduction of out-of-pocket lump-sum payments for prescriptions with multiple drugs and a rise in coinsurance for the elderly from 10% to 20%. Coinsurance rate for heads of households in company-managed insurance, government-managed insurance, seamen's insurance and mutual aid associations' benefit schemes went up to 20% in September 1997 and further increased to 30% (for outpatient care and drugs) in April 2003 (Fig.2, Table 3).

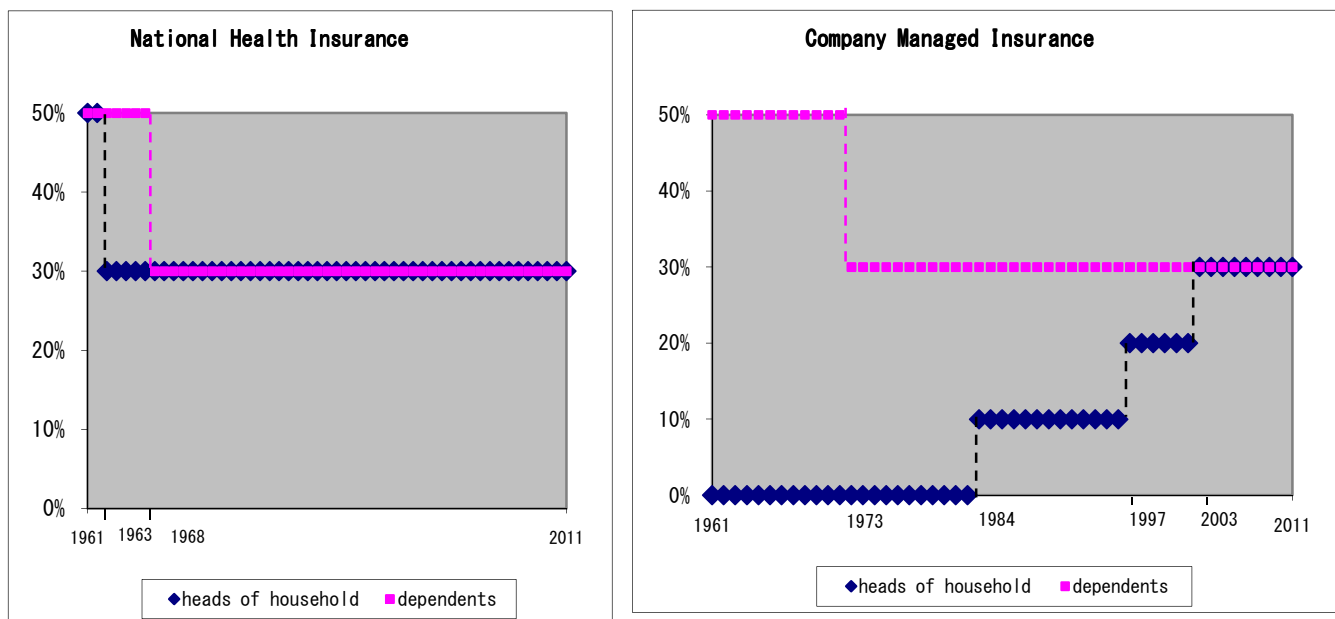


Figure 2. Nominal coinsurance rates in 1961-2011

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

Table 3. Nominal coinsurance rates before and after April 2003 reform

| Health insurance plan | Heads of households | | Dependents | |
|---|----------------------------|--------------|--|--------------|
| | Before | After | Before | After |
| Company-managed insurance; Government-managed insurance; Seamen's insurance; Mutual aid associations | 20% | 30% | 30% for outpatient care; 20% for inpatient care | 30% |
| National health insurance | 30% | 30% | 30% | 30% |

Notes: The Table reports nominal coinsurance rates for enrollees aged 3-69.

Similarly to the findings in international literature, Japanese empirical studies generally demonstrate a negative effect of coinsurance rate on the amount of consumer health care expenditure. Since coinsurance rate is particular to health insurance plan and the choice of health insurance plan is exogenous for Japanese consumers, a few studies exploit pooled data on the users of different plans. However, such analysis commonly employs prefectural (Nishimura, 1987; Maeda, 1978) or insurance association level data (Babazono et al., 2003) which might lead to inaccuracy due to aggregation (Table 4). A number of papers use Japanese microdata to assess the effect of changes in coinsurance rates in a particular plan (Table 5). Yet, the common pattern of studying the behavior of consumers who experienced a change in coinsurance rate provides only limited assessment of the effect. Moreover, such analyses with the data for a certain company (Tokita et al., 2002) or with the data for patients with certain illnesses in a certain company (Babazono et al., 2005) may suffer from selection bias due to sample-specific individual characteristics. Kan and Suzuki (2010, 2006) attempt to employ program evaluation methods by introducing a dummy variable for consumers exposed to a rise in coinsurance rate. Nonetheless, treatment group (heads of households) and control group (dependents) in their approach are not fully comparable since they are likely to differ in such individual characteristics as age and gender.⁶

⁶ Dependents in company-managed insurance commonly include housewives and non-working children.

Table 4. Selected studies estimating the effect of coinsurance rate on health care demand in Japan

| Study | Dependent variables | Sample | Model | Price variable | Price effect |
|--|--|---|---|--|---|
| 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 | Pooled data (simple OLS or the model with serial correlation) | Effective coinsurance rate | Neutral effect in pooled data model in 1974-1978. Negative effect in pooled data models in 1979-1983 and 1974-1983 (but for serial correlation model for in 1974-1983 where price effect is positive for inpatient care). The results refer to the average aggregate data on non-elderly and elderly enrollees. |
| Bhattacharya Votg, Y oshikawa, and Nakahara (1995) | Weeks between outpatient visits (for those with subsequent visits), data censored after 13 weeks | Japanese patient survey data on 437,901 patients in 1990 | Cox proportional hazards model | Expected out-of-pocket expenditure for an outpatient visit | Negative effect. Rise in out-of-pocket expenditure decreases the probability of visiting the doctor Price elasticities for different groups of diseases in the range of -0.54 to -0.12 |
| Kupor, Liu, Lee, Y oshikawa (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 | Cross-section OLS regression in each of the two years | Amount of copayment per patient day in a prefecture | Negative effect. Corresponding coefficients for price variable in regressions in 1984 and 1989 are respectively -0.19 and -0.18 for the aggregate utilization (the sum of three types of health care utilizations), -0.01 and -0.009 for inpatient care, -0.19 and -0.12 for outpatient care, -0.04 and -0.05 for dental care. |
| 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 in other cases. | 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 Ministry of Health, Labor, and Welfare in all 47 prefectures in 1986-1995. | Multinomial probit model, differences in probability model | Equals 1 for 10% coinsurance rate and 0 for 30% coinsurance rate | Negative effect of increase in price for demand for medical services and positive effect for demand for over-the-counter drugs. The marginal effect of price variable is 0.0288 for the demand for medical services and -0.010 for the demand for over-the-counter drugs. |
| Ii and Ohkusa (2002b) | Categorical variable, which equals 1 if a patient demands medical services; 2 if a patient buys over-the-counter medicines and 0 in other cases. | 225 patients aged 22-59, out of 548 respondents of the survey, conducted in Tokyo, Kanagawa, Saitama, Chiba, Osaka, Kyoto, Nara and Hyogo in the period from November 1, 1997 to January 20, 1998. | Multinomial probit, differences in probability model | Nominal coinsurance rate | Negative effect for demand for medical services model, and positive effect for demand for over-the-counter medicines. |

| Study | Dependent variables | Sample | Model | Price variable | Price effect |
|--------------------------|---|---|---|--------------------------|--|
| Babazono et al. (2003) | Case rate (number of monthly bills) for inpatient, outpatient and dental care per 1000 insured; number of service days per case; medical cost per insured born by insurer | 1,797 health insurance associations (company-managed insurance) in 1996 and 1998 (i.e. 6 months before and 6 months after the September 1997 rise in insurance rate of heads of households) | OLS regression (dependent to the insured ratio is among covariates) | Nominal coinsurance rate | Negative effect. The elasticities ¹⁾ of demand with respect to nominal coinsurance rate were: -0.07 for inpatient case rate, -0.05 for outpatient case rate, -0.06 for dental care case rate; -0.05 for inpatient service days, -0.06 for outpatient service days, -0.02 for dental care service days. The elasticities of medical cost per day were: -0.03 for inpatient, -0.13 for outpatient, -0.11 for dental care. The elasticities of medical cost per insured born by insurer were: -0.14 for inpatient care, -0.22 for outpatient care, -0.18 for dental care |
| 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. | Sequential probit model, random effects | Nominal coinsurance rate | Negative albeit insignificant effect |

Note: 1) Recalculation according to the results in Babazono et al. (2003).

Table 5. Selected studies estimating the effect of reforms in coinsurance rate on health care expenditure in Japan

| Study | Reform | Sample | Dependent variables | Model | Main results |
|--|--|---|---|--|---|
| Maeda (1978) | Decrease of coinsurance rate for dependents in company-managed insurance and government-managed insurance from 50% to 30% in October 1973; decrease in coinsurance rate by the elderly from 50% to 0% in January 1973. | Data on government-managed insurance and company-managed insurance. 12,960 and 15,115 households in 1971; 12,431 and 15,184 in 1976 respectively. | Unified fee schedule points a day in outpatient, inpatient and dental care. | OLS regressions with linear time trend and a constant. Separate regressions for pre-reform and post-reform periods for each of the demand variables. | Expansion of benefits resulted in an increase in health care expenditure. For non-elderly households in government-managed insurance the increasing linear trend in daily expenditure in inpatient, outpatient and dental care became faster. For elderly households in government-managed insurance daily expenditure for outpatient and inpatient care increased. |
| Tokita, Hosoya, Hayahashi, Kumamoto (2002) | Increase in coinsurance rate for heads of household, lump-sum payments for drugs in company-managed insurance in September 1997. | Claims data of a large company in 1997 (92,717 households and 161,691 dependents). | Unified fee schedule points per claim. | OLS for pooled monthly data. | Dummy for health care system change (which equals 1 since September 1997) is negatively significant in explaining the number of unified fee schedule points per claim of heads of households. |
| Babazono et al. (2005) | Increase in coinsurance rate for heads of household in company-managed insurance in April 2003. | Claims data for 211 patients with hypertension and 66 patients with diabetes mellitus, patients are insured in one company-managed health insurance association, pre-reform and post-reform data (April-September 2002 and April-September 2003). | Compliance rate (percentage of the months in which drugs were prescribed); number of monthly outpatient visits; monthly outpatient medical expenditure per patient. | Means comparison. | The elasticities ¹⁾ of demand with respect to nominal coinsurance rate are: compliance rate: hypertension without complications -0.04; hypertension with complications -0.04; diabetes without complications -0.40, diabetes with complications -0.04; number of monthly outpatient visits: hypertension without complications -0.13; hypertension with complications -0.25; diabetes without complications -0.17; diabetes with complications 0; monthly outpatient medical expenditure per patient: hypertension without complications 0; hypertension with complications -0.07; diabetes without complications -0.08, diabetes with complications -0.10. |

| Study | Reform | Sample | Dependent variables | Model | Main results |
|-----------------------|---|---|---|--|---|
| Kan and Suzuki (2006) | Increase in coinsurance rate for heads of household and introduction of lump-sum payments for drugs in company-managed insurance in 1997. | Monthly claims data from 111 health insurance associations in April 1996 to November 1999. A random sample, 5% of the individuals in the survey (18,388 heads of households and 17,793 dependents). | Unified fee schedule points per outpatient visit and per inpatient day. | A two-part model. Difference-in-difference estimations with household heads as the treatment group and dependants as the control group. Random effects GLS for outpatient expenditure per visit and daily inpatient expenditure. Random effects probit model for hospital admission rates. | The September 1997 reform had a negative effect on the demand of heads of households for outpatient care. No significant effect on inpatient care is noticed. |
| Kan and Suzuki (2010) | Increase in coinsurance rate for heads of household and introduction of lump-sum payments for drugs in company-managed insurance in 1997 | Monthly claims data from 111 health insurance associations in April 1996 to November 1999. A random sample, 5% of the individuals in the survey (18,326 heads of households and 17,793 dependents) | Unified fee schedule points per outpatient visit. | A two-part model. Difference-in-difference estimations with household heads as the treatment group and dependants as the control group. Random effects GLS for outpatient expenditure per visit. Explanatory variables include medical benefits, fringe benefits, public assistance. | The September 1997 reform had a negative effect on the demand of heads of households for outpatient care. |

Notes: Recalculation according to the results in Babazono et al. (2005). One point in unified fee schedule is equivalent to 10 yen.

3 Empirical models

3.1 Two-part model with latent classes

Duan et al.'s (1983) two-part model considers individuals who make independent decisions about purchasing health care and the amount purchased. Each part of the model is determined by an independent process: a binary choice model estimates the participation decision, and a linear model predicts the amount of health care expenditure conditional on the fact the expenditure is non-negative.⁷ The model treats nominal coinsurance rate as exogenous, and does not provide for consumer selection of health insurance plan.

3.1.1. Panel data binary choice model with latent classes

The model predicts the probability of having health care expenditure. It incorporates a latent class approach (Deb and Trivedi, 1997) which better captures individual heterogeneity than usual models with heterogeneity reflected in individual characteristics. Let

$$y_{it} = \mathbf{x}_{it}' \boldsymbol{\beta}_j + \varepsilon_{it} + u_i, \quad (1)$$

$$z_{it} = \begin{cases} 1 & \text{if } y_{it} > 0 \\ 0 & \text{if } y_{it} \leq 0 \end{cases} \quad (2)$$

$$\varepsilon_{it} \text{ and } u_i \text{ are independent; } \varepsilon_{it} \sim N(0,1); \quad u_i \sim N(0, \sigma_u^2), \quad (3)$$

$$F_j = \frac{\exp \mathcal{G}_j}{\sum_{j=1}^J \exp \mathcal{G}_j}, \quad \mathcal{G}_j = 0, \quad (4)$$

where i is the index for consumers; t is the index for year; j is the index for latent class ($J=2$); z_{it} is a binary variable which equals unity if health care expenditure is positive; y_{it} is health care expenditure; \mathbf{x}_{it} are covariates related to the demand for health care; F_j denotes the probability of belonging to the j -th latent class, and $\boldsymbol{\beta}_j$ are coefficients for j -th latent class.

We assume that the observation remains in the same latent class within the whole period $t=1 \dots T$. Posterior joint probability of belonging to latent class j is estimated as:

$$P(j|i) = \frac{F_{ij} \cdot \prod_{t=1}^T P(i, t | j)}{\sum_{j=1}^J F_{ij} \cdot \prod_{t=1}^T P(i, t | j)}, \quad (5)$$

where F_{ij} is a prior class probability and $P(i, t | j)$ are probabilities of observation i conditional on class j in a period t , T is the final time period. Comparing $P(j|i)$ for all j -s, the most probable latent class is determined.

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

Note that estimating the fitted values of the dependent variable by assigning each observation to the most probable latent class may not be a most accurate approach. Indeed, the classes are “latent” (i.e. not exactly determined) and, thus, the assignment involves an approximation which leads to a certain error.⁸ Therefore, an alternative approach takes a weighted average of the fitted values of each observation in all latent classes (Greene, 2005).

3.1.2 Modeling positive health care expenditure

The model predicts health care expenditure given the expenditure is non-negative. Individual heterogeneity is modeled with a latent class approach, which was shown to provide a better fit of health care expenditure in a group of frequent (high demand) users of health care than linear models (Deb and Holmes, 2000).

Panel data linear model with latent classes

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

$$\log(y_{it}) = \mathbf{x}'_{it} \boldsymbol{\gamma}_j + \zeta_{it} + v_i, \quad (6)$$

$$E v_i = 0; E \zeta_{it} = 0; \zeta_{it} \text{ and } v_i \text{ are non-correlated; } \zeta_{it} \text{ and } \mathbf{x}_{it} \text{ are non-correlated,} \quad (7)$$

where y_{it} is health care expenditure, \mathbf{x}_{it} are covariates related to the demand for health care, j is the index for latent class ($J=2$), $\boldsymbol{\gamma}_j$ are coefficients for j -th latent class, with F_{ij} and $P(i,t|j)$ estimated according to (4) and (5).

Panel data generalized linear models with latent classes

Owing to the retransformation problem in regressions with logged dependent variable (Duan, 1983; Manning, 1998; Mullahy, 1998), estimating linear model (6)-(7) 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 and Wedderburn, 1972; McCullagh and Nelder, 1989; Mullahy, 1998; Blough et al., 1999). Although there are other possible solutions,⁹ the advantages of generalized linear models are improved precision and robustness of the estimate of the conditional mean (Manning and Mullahy, 2001). 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

⁸ Our exercise with Monte-Carlo simulations for 600 individuals demonstrate that the error in terms of assigning the individuals to the classes based on posterior class probabilities is 30 percent in a cross-sectional latent class model.

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-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).

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 gamma, Weibull, and inverse Gaussian families. Let

$$f(E(\mathbf{y}|\mathbf{x})) = \mathbf{x}' \boldsymbol{\beta} \quad (8)$$

$$\mathbf{y}|\mathbf{x} \sim g(\mathbf{y}, \mathbf{x}' \boldsymbol{\beta}, \boldsymbol{\theta}), \quad (9)$$

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).¹⁰ The comparison of the goodness-of-fit between OLS and generalized linear models is conducted with the analysis of residuals (raw bias, mean squared error, and mean absolute prediction error).

The panel data version of equation (11) is the following:

$$f(E(y_{it}|\mathbf{x}_{it})) = \alpha_i + \mathbf{x}_{it}' \boldsymbol{\beta} + u_{it} \quad (10)$$

where $t=1 \dots T$, and α_i may be correlated with \mathbf{x}_{it} .

The generalized linear model with latent classes assumes that

$$f(E(y_{it}|\mathbf{x}_{it}, j)) = f(\mathbf{x}_{it}' \boldsymbol{\beta}_j) \quad (11)$$

where j is the index for latent class, $\boldsymbol{\beta}_j$ are coefficients for j -th latent class, with F_{ij} and $P(i,t|j)$ estimated according to (4) and (5).

3.2 Panel data Tobit model with latent classes

The model deals with the whole sample of observations, predicting health care expenditure in a censored regression, with lower tail censoring at zero. Let

$$w_{it}^* = \mathbf{x}_{it}' \boldsymbol{\delta}_j + \xi_{it} + \psi_i, \quad (12)$$

$$\xi_{it} \text{ and } \psi_i \text{ are independent; } \xi_{it} \sim N(0, \sigma_{\xi}^2); \quad \psi_i \sim N(0, \sigma_{\psi}^2), \quad (13)$$

$$w_{it} = \begin{cases} w_{it}^* & \text{if } w_{it}^* > 0 \\ 0 & \text{if } w_{it}^* \leq 0, \end{cases} \quad (14)$$

where $w_{it} = \log(1 + y_{it})$, y_{it} is health care expenditure, \mathbf{x}_{it} are covariates related to the demand for health care, j is the index for latent class ($J=2$), $\boldsymbol{\delta}_j$ are coefficients for j -th latent class, with F_{ij} and $P(i,t|j)$ estimated according to (4) and (5).

¹⁰ See derivation of model deviance and deviance residuals in the Appendix.

An alternative approach of exploiting the whole sample is the use of exponential conditional mean model (Jones, 2000). However, neither the one-step nor the two-step estimators of the exponential conditional mean model (Jones, 2000; Mullahy, 1998) fit our data.

3.3 Latent class 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)”:

$$L = 2 (\ln L_u - \ln L_R) \sim \chi^2 ((J - 1) \cdot (k + 1)), \quad (15)$$

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.¹¹ It should be noted that the LR test did not reject the null hypothesis of the model with latent classes in all other estimations (i.e. in case of panel data logit model, panel data linear model, panel data GLM model, and panel data Tobit model). Therefore, to choose between the models with and without latent classes, we use both Greene’s (2007) LR test and Akaike and Schwarz information criteria. We follow Greene (2007) and apply the following formulas for information criteria:

$$AIC = -2(\log L - k)/N,$$

$$BIC = -2(\log L - k \log k)/N,$$

where N is the number of observations.

3.4 Average treatment effect

Conditional average treatment effect in a latent class model

The treatment group is respondents who experienced a rise in coinsurance rate due to 2003 reform: heads of households in company-managed insurance, government-managed insurance, and mutual aids associations’ benefit schemes.¹² The control group consists of enrollees in national health insurance, and dependents in company-managed insurance, government-managed insurance, seamen’s insurance, and mutual aid associations’ health insurance plans. The control group is constructed to match the treatment group in the major parameters related to the demand for health care: income, age, gender, and health condition (Deb and Trivedi, 2011; Bago d’Uva and Jones, 2009; Jones et al., 2007; Deb and Holmes,

¹¹Greene (2007) “Testing for the Latent Class Model”. In: LIMDEP. Version 9.0. Econometric modeling guide. Vol.1. E17.10.5.

¹² There are no consumers with seamen’s health insurance in our sample.

2000). Separate analyses are done for each of the two latent classes, with posterior probability of latent class membership estimated in linear model or Tobit model.¹³

Our approach mimics the methodology for employing analytical methods for non-randomized treatment assignment. Note that the above chosen parameters related to the demand for health care are not affected by the treatment, which is a necessary identification condition for the analysis (Angrist and Pischke, 2009; Imbens, 2004). While a number of methods measuring average treatment effect for non-randomized treatment assignment exist in the literature (see review in Imbens, 2004), we use nearest neighbor matching with replacement, which does not depend on smoothing parameters and enables raising precision through increasing the number of matches (Abadie et al., 2004).¹⁴ Average treatment effect, conditional on the sample distribution of covariates (CATE) is estimated as (Imbens, 2004; Abadie and Imbens, 2002):

$$\overline{\tau(X)} = \frac{1}{N} \sum_{i=1}^N E[y_i(w_i=1) - y_i(w_i=0) | \mathbf{X}], \quad (16)$$

where $i = 1 \dots N$ is the observed sample; y_i is the outcome; w_i is the treatment indicator which equals one under the active treatment, and zero under the control; \mathbf{X} are parameters related to the demand for health care. Using the STATA module `nnmatch` (Abadie et al., 2004) we correct for the asymptotic variance of matching estimators (Abadie and Imbens, 2002) by matching and regression.

The outcome in our analysis is the amount of health care expenditure (taken in logs). First, we measure CATE in the reform year (2003). Second, to distinguish between the immediate effect of the reform and the effect in the medium run, we study the difference between the average value of the outcome in the S post reform years and the value in the pre-reform year (2002). Let

$$Dy_{iS} = \frac{1}{S} \sum_{s=1}^S y_{i,2002+s} - y_{i,2002} \quad (17)$$

where i is the index for consumers, y_{it} is log of medical CPI adjusted health care expenditure in September of year t , S is the number of post-reform years. Each corresponding covariate is taken in the form

$$Dx_{iS} = \frac{1}{S} \sum_{s=1}^S x_{i,2002+s} - x_{i,2002} \quad (18)$$

Note that collapsing the data into the pre-reform (in this case, the year 2000) and the post-reform period enables to solve the problem of serial correlation in difference-in-difference estimations (Bertrand et al., 1996).

¹³ Consumers did not separate into latent classes in the generalized linear models.

¹⁴ However, increased precision comes at the cost of bias of the estimator. Therefore, we used the models with 3 matches, which provided for most robust results.

Unconditional average treatment effect in a latent class model

Finally, we use the conventional approach of measuring average treatment effect of the reform in unconditional difference-in-difference estimations. For observations with $y_{it} > 0$, let

$$\log(y_{it}) = \mathbf{x}'_{it} \boldsymbol{\theta}_j + T_{it} \tau_j + D_{it} \eta_j + D_{it} T_{it} \lambda_j + v_i; \quad E v_i = 0, \quad (19)$$

where T_{it} is a treatment indicator, which equals unity in the post-reform period and zero in the pre-reform period; D_{it} is a reform dummy, which equals unity for the treated and zero for controls; $E \zeta_{it} = 0$; where y_{it} is health care expenditure, \mathbf{x}_{it} are covariates related to the demand for health care,¹⁵ j is the index for latent class ($J=2$), with F_{ij} and $P(i,t|j)$ estimated according to (4) and (5). In this formulation, $(\tau_j + \lambda_j)$ is the average treatment effect of the reform (for the treated) and λ_j is difference-in-difference in the values of the dependent variable of the treated and the controls (Greene, 2012).

4 Data

4.1 Survey

The Japanese Panel Survey of Consumers is established in 1993 as the first longitudinal study to accumulate representative micro data on Japanese individuals. The data are collected through the surveys of young women who answer questions about themselves and the members of their households. The major advantage of the Japanese Panel Survey of Consumers for the purposes of analyzing consumer demand for health care is its longitudinal character, the presence of a large number of individual parameters, the existence of questions on the type of health insurance and on the amount of health care expenditure.

At the same time, the usage of the database faces a number of restrictions. The question on total health care expenditure is formulated in the questionnaire as “health insurance expenditure” which includes expenditure on medical services, drugs, and health goods.¹⁶ In this formulation health care expenditure may incorporate the cost of health goods not covered by health insurance. We measured the average share of expenditure on health goods outside health insurance in total consumer health care expenditure using the 2008 data for Japan Household Panel Survey (wave 1, 2009) and focusing on young single women without children who did not turn for inpatient care.¹⁷ The estimated share was 0.35, which implies a bias in the dependent variable. However, we assume that the share of expenditure on health

¹⁵ Coinsurance rate is not included in \mathbf{x}_{it}

¹⁶ Arguably, health insurance premiums are not regarded as a potential component of “health insurance expenditure”, asked in the question of Japanese Panel Survey of Consumers. Indeed, the prevalence of zero reported health care expenditure among heads of household, who pay premiums and hence can not have zero health care expenditure if premiums are considered a part of expenditure, was 47.0%. Moreover, Japan Household Panel Survey, which has a similar question on “health insurance expenditure”, introduces a special question on the amount of premiums.

¹⁷ Since by construction of our sample, respondents of Japanese Panel Survey of Consumers who turned for inpatient care are excluded from the analysis.

goods not covered by health insurances is not related to coinsurance rate. Indeed, health goods outside health insurance (vitamins, contact lenses, etc.) are unlikely to be complements or substitutes of health care provided within health insurance. This assumption allows imputing average expenditure outside health insurance and calculating average price elasticity.

Another restriction deals with gender bias. Since the data on health care demand which can be retrieved from Japanese Panel Survey of Consumers deals with out-of-pocket expenditure paid personally by the respondent, our analysis became limited to women. However, women generally pay more attention to health condition than men, and therefore, health care expenditure by women may be higher than that of the general population of the corresponding age.

The final restriction is age bias. Indeed, the Japanese Panel Survey of Consumers monitors women of young age. However, young people have fewer health problems, lower income, and tend to be less concerned about health, which makes their demand more sensitive to health care prices (Yoshida and Takagi, 2002).

4.2 Sample

For the purposes of analyzing health care expenditure we restrict the sample of Japanese Panel Survey of Consumers to rounds 8-16 (2000-2008). In fact, health care expenditure is reported in Japanese Panel Survey of Consumers since round 6 (1998). However, respondents are asked to provide subjective assessment of their health condition only since round 10 (2002). The value of round 10 could be used for the missing values for health condition in preceding rounds. Yet, the imputed values might be imprecise since subjective assessment of health condition is likely to be related to age, lifestyle, and other parameters. Nonetheless, using the data for rounds 10-16 we find that the actual value and the forwarded value of the binary variable for low health condition (computed on the basis of the answers to the questions on subjective health assessment, see Table 5) in case of one-, two- or three-year lag differed correspondingly for 7.2%, 9.8%, and 10.9% of respondents. Choosing the 10% level of precision, we fill the missing data for subjective assessment of health conditions only for the two rounds (8 and 9) and limited our sample to rounds 8-16.

The dependent variable “health care” is total health care expenditure for outpatient services and drugs, measured as the number of unified fee schedule points. The variable is obtained by dividing consumer health care expenditure by nominal coinsurance rate and then, dividing by 10.¹⁸ It should be noted that owing to the system of medical benefits and medical expenditure deductions, consumer price for health

¹⁸A point in unified fee schedule is equivalent to 10 yen.

care may turn out to be lower than nominal coinsurance rate. Yet, various benefits and exemptions mostly apply to inpatient care, which is not studied in our analysis.¹⁹

Variable “coinsurance rate” is constructed to reflect the size of nominal coinsurance rate for outpatient services and drugs.²⁰ Coinsurance rate equals zero for heads of households in company-managed health insurance,²¹ and mutual aid associations’ benefit schemes in rounds 8-10. This corresponds to a 20% nominal coinsurance rate. Coinsurance rate equals unity for users of national health insurance in rounds 8-16; for dependents in company-managed health insurance and mutual aid associations’ benefit schemes in rounds 8-16; for heads of households in company-managed health insurance and mutual aid associations benefit schemes in rounds 11-16. Note that enrollment as head of household or dependent is specified in the questionnaire since round 12. Therefore, we assume that a respondent was insured as head of household in company-managed health insurance or in mutual aid associations benefit schemes in rounds 8-11 if she worked in the corresponding year. We assess this assumption by using the actual data for rounds 12-16 and find that it held in 99.2% of cases for company-managed health insurance and in 98.9% of cases for mutual aid associations’ benefit schemes.

Table 5. Descriptive statistics for the unbalanced panel in 2000-2008

| Variable | Definition | Obs | Mean | St.Dev. | Min | Max |
|------------------|--|------|-------|---------|-----|--------|
| health care | unified fee schedule points in September of the corresponding year (adjusted for medical goods and services CPI, in 2005 real terms) | 3456 | 1960 | 14980 | 0 | 510215 |
| age | age as of March of the corresponding year | 3456 | 30.98 | 5.21 | 24 | 49 |
| income | total household income a year, thousand yen (adjusted for goods and services CPI, in 2005 real terms) | 3360 | 7237 | 5833 | 0 | 95924 |
| 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” | 3407 | 0.10 | 0.30 | 0 | 1 |
| coinsurance rate | = 1 if nominal coinsurance rate for outpatient health care and drugs is 30%; 0 otherwise | 3456 | 0.85 | 0.36 | 0 | 1 |
| participation | = 1 if health care expenditure is positive; 0 otherwise | 3456 | 0.47 | 0.50 | 0 | 1 |

¹⁹ Indeed, using the data from Japan Household Panel Survey for young single women without children who did not turn for inpatient care, we estimated that only 2.4 % of them applied for medical care benefits and 11.0% requested medical expenditure deductions.

²⁰ By construction our sample excluded people who had an illness that required hospitalization. Therefore, the analysis does not deal with nominal insurance rates for inpatient care.

²¹ The category “company-managed insurance” in the questionnaire encompasses company-managed insurance and government-managed insurance.

The number of respondents in rounds 8-16 varies from 1,376 to 2,284. Since health care expenditure in Japanese Panel Survey of Consumers is not subdivided with regards to the household member it is paid for, our analysis deals with the sample of single women without children. Furthermore, to construct the variable “coinsurance rate”, we analyze observations with non-missing answers on the type of health insurance.²² This decreases the sample to 234-724 respondents a year. The exclusion of women with serious health problems (depression or an illness that required hospitalization)²³ limits the sample to 212-631 observations a year. We estimate the effect of coinsurance rate on health care expenditure which requires the use of truncated sample with 107-272 observations a year.

Moreover, difference-in-difference estimations are possible with a balanced panel and a truncated sample (i.e. positive health care expenditure in the years 2002 to 2002+S, $S>0$). The preconditions decreases the numbers of treated and controls. Indeed, the size of balanced panel shrinks with years owing to two reasons. The first deals with the inability to find respondents of the previous round due to their migration. The second is explained by the construction of our sample of single women – women get married in subsequent rounds of the survey. Furthermore, truncation induces additional restriction on the number of observations. Consequently, we conduct difference-in-difference estimations for only two post-reform years (S equals 1 or 2).

The small sample size becomes a limitation of our estimations. As for the analysis of conditional average treatment effect, we face another restriction dealing with the small size of the control group. Indeed, we construct the control group from the users of national health insurance and from dependents in company-managed insurance and mutual aid associations benefit schemes. However, the users of national health insurance constitute only 23.3% of young women in Japanese Panel Survey of Consumers. As for dependents in company-managed insurance and mutual aid associations’ benefit schemes, they are commonly housewives who are not included in our sample of single women.

²² The type of health insurance was not reported by 3-13% of respondents in various years.

²³ The exclusion is not conducted for cohort C in 2003 and cohort D in 2008, since the questionnaires for cohort C and D in corresponding years in do not contain the questions on depression or an illness that required hospitalization. (See Appendix for the description of the sampling procedures and the cohorts.)

5 Empirical results

5.1 Price effect in a binary choice model

The results of the test for normality of errors in a panel data probit model²⁴ rejected the hypothesis of normality, consequently, we used logit model for binary choice equation in the two-part model. The size of marginal effect is -0.015, which implies that a rise in nominal coinsurance rate from 20% to 30% decreases the probability of having health care expenditure by 1.5% (Table 6). The value of the marginal effect corresponds to the results of the previous studies (Ii and Ohkusa 2002a).

Marginal effects of coinsurance rate are different in each of the latent classes.²⁵ Yet, in both classes marginal effects of coinsurance rate, as well as marginal effects of most other variables, are statistically insignificant. Along with the fact that prior class probabilities are close to 50% for each class, this implies that Japanese young single women do not separate into latent classes with respect to their decision on consuming outpatient health care services and drugs.

Table 6. Marginal effects in the panel data logit model

| | (1) | (2) | |
|---|---------------------------------------|----------------------|---------------------|
| | Whole sample | Latent class 1 | Latent class 2 |
| log income | 0.0101 (.0303) | 0.0278 (0.2061) | 0.0873 (0.2585) |
| log age | 1.1714 (0.1497)*** | 0.8888 (0.5150)* | 0.5059 (0.4731) |
| coinsurance rate | -0.0148 (0.1425·10 ⁻⁷)*** | 0.0102 (0.0565) | 0.0136 (0.0560) |
| lowhcond | 0.0802 (0.6858·10 ⁻⁷)*** | 0.0011 (0.0674) | 0.1464 (0.0740)** |
| constant | | -11.6151 (2.0740)*** | -9.7089 (2.0613)*** |
| Log likelihood | -1195.577 | -2104.310 | -2104.310 |
| AIC | 1.029 | 1.284 | 1.284 |
| BIC | 1.954 | 1.304 | 1.304 |
| Observations | 3295 | | |
| Individuals in the unbalanced panel | 1055 | | |
| Prior probabilities of class membership | | 0.4998 | 0.5002 |

*** p< 0.01, ** p< 0.05, *p< 0.1. Robust standard errors in parentheses

Notes: Dependent variable is *participation*. “Log” denotes logarithm of a corresponding explanatory variable. Latent class 1 denotes “high intensity users”, latent class 2 denotes “low intensity users”. Time dummies proved insignificant and were excluded from the list of covariates. Marginal effects are estimated at sample means. In the unconditional fixed effects model, estimated in LIMDEP, covariates do not include constant since the model fits a complete set of constants for groups of observations over time (Greene, 2007). According to the results of the Hausman test, unconditional fixed effects model was preferred to random effects model.

²⁴ We computed the fitted values of the dependent variable, incorporating the estimates of individual’s fixed effects, and then implemented the cross-section version of the test as specified in Greene (2007) “A Test for Normality in the Probit Model” In: LIMDEP 9.0. Econometric modeling guide. Vol.1. E18.60.

²⁵ Latent class estimations are conducted in the framework of random effects model.

5.2 Health care expenditure

Linear model

The results with the linear model reveal that nominal coinsurance rate is negative and significant in the whole sample and in each latent class.²⁶ The magnitude of the effect of nominal coinsurance rate is higher in the latent class of frequent users (Table 7).

Table 7. Estimating panel data linear model for health care expenditure

| | (3) | | (4) | | | |
|--|--------------|-------------|----------------|-------------|----------------|-------------|
| | Whole sample | | Latent class 1 | | Latent class 2 | |
| log income | 0.0927 | (0.0317)*** | -0.2491 | (0.1235)** | 0.1269 | (0.0339)*** |
| log age | 0.6822 | (0.1420)*** | 0.6720 | (0.3518)* | 0.6631 | (0.1508)*** |
| coinsurance rate | -0.3713 | (0.0640)*** | -0.4674 | (0.1350)*** | -0.3635 | (0.0698)*** |
| lowhcond | 0.1203 | (0.0742) | 0.2305 | (0.2817) | 0.1027 | (0.0861) |
| constant | 4.7888 | (0.5999)*** | 8.5774 | (1.9013)*** | 4.3675 | (0.6422)*** |
| Log likelihood | -1365.832 | | -2029.691 | | -2029.691 | |
| AIC | -0.192 | | 2.605 | | 2.605 | |
| BIC | 1.752 | | 2.650 | | 2.650 | |
| Observations | 1568 | | | | | |
| Individuals in the unbalanced panel | 663 | | | | | |
| Prior probability for class membership | | | 0.2109 | | 0.7891 | |

*** p< 0.01, ** p< 0.05, *p< 0.1. Robust standard errors in parentheses

Notes: Dependent variable is *log(healthcare)*. Observations with zero value of health care expenditure are excluded from the analysis. “Log” denotes logarithm of a corresponding explanatory variable. Latent class 1 indicates “high intensity users”, latent class 2 denotes “low intensity users”. Time dummies proved insignificant and were excluded from the list of covariates. In the unconditional fixed effects model, estimated in LIMDEP, covariates do not include constant since the model fits a complete set of constants for groups of observations over time (Greene, 2007). According to the results of the Hausman test, random effects model is preferred to unconditional fixed effects model. In case of linear regression without latent classes $AIC=(\log L-k)(n/2)-(1+\log 2\pi)$.²⁷

Generalized linear models

The results of heteroscedasticity and normality of errors tests show that the errors in the panel data OLS model are heteroscedastic and nonnormal.²⁸ Consequently, we experiment with generalized linear models with several distribution families. We find that exponential distribution provides the best fit in terms of raw bias, mean squared error and mean absolute prediction error (Table 8).

²⁶ It should be noted that although Greene’s (2007) LR test did not reject the null hypothesis about the validity of the model with latent classes, the values of information criteria is smaller in the model without latent classes than in the model with latent classes.

²⁷ Greene (2007), “The Linear regression model”, in: LIMDEP Version 9.0: Econometric Modeling Guide, Vol.1, E5-4.

²⁸ Note, however, that the hypothesis of normality of residuals is rejected for standardized deviance residuals and Anscombe residuals, calculated for GLM with latent classes and the three analyzed distribution families: exponential, Weibull and gamma. Yet, the values of skewness/kurtosis for each residual for exponential distribution family in the GLM model with latent classes are close to the parameters of the normal distribution.

Table 8. Residuals in the panel data models for health care expenditure

| | Linear model | GLM, exponential distribution | GLM, Weibull distribution | GLM, gamma distribution |
|----------|--------------|-------------------------------|---------------------------|-------------------------|
| Raw bias | 0.0005 | -44.7766 | -221.8056 | 3854.45 |
| MSE | 0.0005 | 40249.72 | 54193.15 | 214006.1 |
| MAPE | 0.7063 | 1549.352 | 1848.73 | 3854.449 |

Notes: In the linear model dependent variable $\log(\text{healthcare})$. In the GLM models dependent variable is *health care*, the link function is logarithm. GLM model with inverse Gaussian distribution family does not converge.

Therefore, we estimate a generalized linear model with latent classes for exponential distribution family.²⁹ According to the results of the estimations with a panel data GLM, coinsurance rate is a significant covariate in the whole sample and in the latent class of infrequent users (Table 9).

Note that the prior probability of the membership in the first latent class is 2 percent, and the number of observations in the first latent class in each round varies from 1 to 6. Consequently, along with accepting the result that individuals separate into two latent classes in the GLM model, we may alternatively conclude that the observations in the first latent class may be considered outliers with extremely high value of health care expenditure.

Table 9. Estimating the panel data generalized linear model for health care expenditure.

| | (5) | | (6) | | | |
|--|--------------|-------------|----------------|----------------|-----------|-------------|
| | Whole sample | | Latent class 1 | Latent class 2 | | |
| log income | 0.0513 | (0.0842) | 3.0990 | (0.4266)*** | -0.1170 | (0.0363)*** |
| log age | -0.7608 | (0.6453) | 0.9484 | (1.1904) | -0.5463 | (0.1693)*** |
| coinsurance rate | 0.3601 | (0.1236)*** | 0.4257 | (0.4001) | 0.3179 | (0.0763)*** |
| lowhcond | -0.3008 | (0.1517)** | 1.5328 | (0.5549)*** | -0.1114 | (0.0871) |
| constant | | | -39.7891 | (5.1523)*** | -5.3321 | (0.7021)*** |
| Log likelihood | -13976.23 | | -14164.63 | | -14164.63 | |
| AIC | 18.678 | | 18.081 | | 18.081 | |
| BIC | 20.957 | | 18.119 | | 18.119 | |
| Observations | 1568 | | | | | |
| Individuals in the unbalanced panel | 663 | | | | | |
| Prior probability for class membership | | | 0.0232 | | 0.9768 | |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses

Notes: Dependent variable is *healthcare*, the link function is log, the distribution family is exponential. In the unconditional fixed effects model, estimated in LIMDEP for the whole sample, covariates do not include constant since the model fits a complete set of constants for groups of observations over time (Greene, 2007).

Note that a positive sign of a coefficient in the GLM model must be interpreted as a negative effect of the corresponding covariate. For easier interpretation of the results, we calculate marginal effects (Table 10), which have reverse signs. The values of the marginal effects demonstrate that a rise in coinsurance rate decreases outpatient health care expenditure in the whole sample and in the class of infrequent users.

²⁹ The latent class model in this paper does not assume that F_{ij} depend on any time invariant consumer characteristics z_i , and therefore, it is essentially a pooled data model. Therefore, the formulas derived for deviance residuals and Anscombe residuals in a cross-sectional case (see Appendix B), may be applied for our panel data GLM model with latent classes.

Table 10. Marginal effects in the panel data generalized linear model for health care expenditure

| | (7) | (8) | |
|------------------|-------------------------|--------------------------|--------------------------|
| | Whole sample | Latent class 1 | Latent class 2 |
| log income | 126.4287 (110.9670) | -32413.527 (13243.851)** | 465.5229 (150.2104)*** |
| log age | 1523.2864 (500.0177)*** | -9919.8366 (12268.811) | 2173.2279 (710.6579)*** |
| coinsurance rate | -953.8593 (222.3264)*** | -10379.364 (10975.134) | -3046.4297 (855.7474)*** |
| lowhcond | 218.1615 (256.3854) | -64883.489 (26224.425)** | 1159.1759 (951.8108) |

*** p< 0.01, ** p< 0.05, *p< 0.1. Robust standard errors in parentheses

Notes: Dependent variable is *healthcare*, the link function is log, the distribution family is exponential. Marginal effects for continuous variables are calculated as $-E[y_i|x_i]\beta$, where β are estimated coefficients. Marginal effects for each binary variable x_k are calculated as $E[y_i|x_i]_{x_k=1} - E[y_i|x_i]_{x_k=0}$

Tobit model

The estimations with the Tobit model demonstrate that nominal coinsurance rate is a negative and significant determinant of health care expenditure only in the latent class of frequent users (Table 11).

Table 11. Estimating Tobit panel data model for health care expenditure

| | (9) | (10) | |
|--|---------------------|--------------------|----------------------|
| | Whole sample | Latent class 1 | Latent class 2 |
| log income | 0.1209 (0.2660) | 0.0631 (0.0564) | 1.2302 (0.2372)*** |
| log age | 10.6690 (2.0783)*** | 0.5714 (0.1811)*** | 11.5028 (1.4774)*** |
| coinsurance rate | -0.4001 (0.4132) | -0.2827 (0.1102)** | 0.4282 (0.4713) |
| lowhcond | 0.8777 (0.4835)* | 0.1460 (0.1337) | 1.1790 (0.5324)** |
| constant | | 5.4022 (0.8530)*** | -52.0030 (6.6299)*** |
| Log likelihood | -5407.424 | -5913.015 | -5913.015 |
| AIC | 3.688 | 3.597 | 3.597 |
| BIC | 4.924 | 3.621 | 3.621 |
| Observations | 3295 | | |
| Individuals in the unbalanced panel | 1055 | | |
| Prior probability for class membership | | 0.2096 | 0.7904 |

*** p< 0.01, ** p< 0.05, *p< 0.1. Robust standard errors in parentheses

Notes: Dependent variable is $\log(1+\text{healthcare})$. “log” denotes logarithm of a corresponding explanatory variable. Latent class 1 indicates “high intensity users”, latent class 2 denotes “low intensity users”. Time dummies proved insignificant and are excluded from the list of covariates. In the unconditional fixed effects model, estimated in LIMDEP for the whole sample, covariates do not include constant since the model fits a complete set of constants for groups of observations over time (Greene, 2007). According to the results of the Hausman test, unconditional fixed effects model is preferred to random effects model.

If we assign observations to the most probable latent class and examine the fitted values for health care expenditure, the results with the linear model and the GLM model show that the amount of health care expenditure in the latent class of frequent users is 2-6 times higher than in the latent class of infrequent users. As for the Tobit model, consumers separate into a class with the (average) positive value of health care expenditure, and the class with zero health care expenditure (Table 12).

Table 12. Average health care expenditure (fitted values)

| | Linear model | | Tobit model | | GLM model | |
|-----------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | Latent class 1 | Latent class 2 | Latent class 1 | Latent class 2 | Latent class 1 | Latent class 2 |
| Round 8 (2000) | 6070 | 2128 | 2597 | 0 | 101431 | 3476 |
| Round 9 (2001) | 6153 | 2255 | 2707 | 0 | 20835 | 3666 |
| Round 10 (2002) | 5967 | 2331 | 2740 | 0 | 23384 | 3716 |
| Round 11 (2003) | 3907 | 1586 | 1991 | 0 | 21398 | 2690 |
| Round 12 (2004) | 3997 | 1610 | 2082 | 0 | 15595 | 2744 |
| Round 13 (2005) | 4097 | 1641 | 2149 | 0 | 6839 | 2769 |
| Round 14 (2006) | 3934 | 1696 | 2230 | 1 | 11955 | 2850 |
| Round 15 (2007) | 4245 | 1756 | 2300 | 2 | 32088 | 2928 |
| Round 16 (2008) | 4261 | 1588 | 1975 | 1 | 28951 | 2704 |

Note: Each cell presents the fitted value of medical CPI adjusted health care expenditure in September of corresponding year, measured in points in unified fee schedule. Latent class 1 denotes “high intensity users”, latent class 2 denotes “low intensity users”.

5.3 Average treatment effect

Conditional average treatment effect

The estimations in model (15) reveal that average health care expenditure in September 2003 is 2528 unified fee schedule points in the treatment group and 3627 points in the control group (the fitted value in the linear model). This implies that given a consumer had health care expenditure, the rise in nominal coinsurance rate from 20% to 30% decreased her average amount of health care expenditure by 30.3%, which is equivalent to price elasticity of -0.6060 . The price elasticity of health care expenditure is -0.6074 in the latent class of frequent users, and -0.0921 in the latent class of infrequent users. Our finding that Japanese consumers with higher demand for health care are more price elastic corresponds to the results in Deb and Trivedi (2002) with the data for RAND Health Insurance Experiment.

The CATE coefficient in the first post-reform year (i.e. in 2003) is negative and significant (Table 13), which implies that compared to the control group with similar socio-demographic characteristics, the amount of health care expenditure of the treatment group decreases after the rise in nominal coinsurance rate.

Table 13. Coefficients of conditional average treatment effect (CATE) by latent classes

| | Linear model | | Tobit model | | |
|--------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | Whole sample | Latent class 1 | Latent class 2 | Latent class 1 | Latent class 2 |
| CATE | -0.3450 (0.1375)** | -0.3151 (0.2075) | -0.0985 (0.1390) | -0.0561 (0.1977) | -0.3506 (0.1976)* |
| Observations | | | | | |
| Treated | 192 | 24 | 168 | 74 | 118 |
| Controls | 56 | 16 | 40 | 24 | 32 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses

Notes: Dependent variable is $\log(\text{healthcare})$. Matching variables and variables for bias correction are logarithm of CPI adjusted-income and logarithm of age. Exact matching is conducted according to the variable *lowhcond* (the value as of 2003). 3 matches are used in the estimations. Latent class 1 denotes “high intensity users”, latent class 2 denotes “low intensity users”.

To estimate price elasticity of expenditure covered by health insurance, we impute the average amount of health care expenditure not covered by health insurance using Japan Household Panel Survey. We assume that the amount of health care expenditure covered by health insurance is a function of nominal coinsurance rate, and the amount of health care expenditure not covered by health insurance does not depend on nominal coinsurance rate.³⁰ Let

$$h = y - \alpha, \quad (20)$$

where h is health care expenditure covered by health insurance, y is total health care expenditure, and α is health care expenditure not covered by health insurance.

Since α does not depend on nominal coinsurance rate, the average values of α are the same for the treated and the controls. Therefore, the average decrease in h due to the reform is

$$\frac{\Delta h}{h} = \frac{\bar{h}_{treated} - \bar{h}_{controls}}{\bar{h}_{controls}} = \frac{\bar{y}_{treated} - \bar{y}_{controls}}{\bar{y}_{controls} - \bar{\alpha}}, \quad (21)$$

where $\bar{y}_{treated}$ and $\bar{y}_{controls}$ are average values of health care expenditure for the treatment and the control groups respectively, and $\bar{\alpha}$ is the average value of health care expenditure not covered by health insurance.³¹

The estimated decrease in the average amount of health care expenditure covered by health insurance is 26.12%, which is equivalent to price elasticity of -0.5225.

Difference-in-difference estimations in model (17)-(18) reveal that the reform effect is insignificant (Table 14), which contradicts the finding on the long-term effect of the change in coinsurance rate (Scitovsky, 1977). However, the insignificance may be due to the small sample size.

Table 14. Coefficients of conditional average treatment effect (CATE) in difference-in-differences estimations

| | Dy ₁ | Dy ₂ |
|--------------|-------------------|-------------------|
| CATE | -0.217 (0.326) | -0.170 (0.248) |
| Observations | | |
| Treated | 49 | 32 |
| Controls | 17 | 11 |

*** p< 0.01, ** p< 0.05, *p< 0.1. Robust standard errors in parentheses

Notes: Dy₁=y₂₀₀₃- y₂₀₀₂; Dy₂=0.5(y₂₀₀₃+ y₂₀₀₄) - y₂₀₀₂, where y_t is log(*health care*). Matching variables and variables for bias correction are logarithm of CPI adjusted-income and logarithm of age. Exact matching is conducted according to the variable *lowhcond* (the value as of 2003). 3 matches are used in the estimations.

³⁰ Moreover, our estimations with Japan Household Panel Survey demonstrated that in case of young single women without children, who did not turn for inpatient care, the share of health care expenditure not covered by health insurance in consumer health care expenditure did not depend on such individual parameters as age and income. The Spearman rank correlation between the share and the binary variable for low health condition was significant at 0.05 level, yet the value of rank correlation coefficient was low: -0.1846.

³¹ Since the 2009 wave of Japan Household Panel Survey deals with the data for 2008, the average value of health care expenditure not covered by health insurance was adjusted by CPI for medicines and health fortification in 2008.

Unconditional average treatment effect

The estimations in the unconditional model (19) reveal that the average treatment effect of the reform is stronger in the latent class of the frequent users (Table 15). At the same time, in the DiD estimations, the average treatment effect is significant only in the class of infrequent users.

Table 15. Coefficients of the unconditional average treatment effect

| | Whole sample | Latent class 1 | Latent class 2 |
|------------------------|---------------------|---------------------|---------------------|
| ATE for the treated | -0.3541 (0.0658)*** | -0.5867 (0.1471)*** | -0.3348 (0.0633)*** |
| ATE in DiD estimations | -0.2081 (0.1309) | 0.0030 (0.2764) | -0.2583 (0.1270)** |
| Observations | | | |
| Treated | 1189 | 185 | 1004 |
| Controls | 379 | 69 | 310 |

*** p < 0.01, ** p < 0.05, *p < 0.1. Robust standard errors in parentheses

Notes: The Table presents the sum of coefficients $\tau + \lambda$ (ATE) and the coefficient λ (ATE in DiD estimations) in a pooled data regression (19), where dependent variable is the logarithm of medical CPI adjusted-health care expenditure in September of year t . Latent class 1 and latent class 2 denote, correspondingly, “high intensity users” and “low intensity users”, estimated in the linear model with latent classes.

6 Discussion

Although out-of-pocket expenditure commonly has a negative effect on the demand for health care (Cutler, 2002), in some countries there may be exceptions to this general pattern (Schreyogg and Grabka, 2010). Similarly, there are exceptions to the general finding on significant price effect of coinsurance rate in Japan (Bessho and Ohkusa, 2006).

The estimations in this paper show that the effect of nominal coinsurance rate on total health care expenditure of Japanese young women is negative and significant. To compare our findings with other Japanese studies we compute the effect of nominal coinsurance rate on the probability of having outpatient health care expenditure, using the results in Ii and Ohkusa (2002a). The coinsurance rate in Ii and Ohkusa (2002a) is a binary variable which equals unity for a 10% nominal coinsurance rate and zero for a 30% nominal coinsurance rate. The authors estimate that the marginal effect of the coinsurance rate for the probability of demanding medical services equals 0.029, and the marginal effect for the probability of buying over-the-counter drugs is -0.010. The multinomial probit model applied by the authors to the choices of seeking medical services or buying over-the-counter drugs (as opposed to doing nothing) uses the same list of covariates in measuring each of the marginal effects. Therefore, the sum of the two marginal effects gives the marginal effect of nominal coinsurance rate on the binary choice for having outpatient health care expenditure. The resulting value of 0.019 implies that a rise of coinsurance rate from 10% to 30% decreases the probability of having outpatient health care expenditure by 1.9%. The half the figure (0.95%) is close to our estimate (1.5%) for half the change in

coinsurance rate: from 20% to 30%. In other words, the response to a rise in nominal coinsurance rate in moderate intervals may be considered close to linear in Japan.³²

Overall, the results of our estimations reveal that regulating consumer demand by the means of coinsurance rate proves to be an effective policy for cost containment in Japan. Yet, the effect is primarily noticeable among the consumers with high demand for health care, who account for 20 percent of our sample. It should be noted that our finding with the latent class models with Japanese data, where the assignment of insurance plans is exogenous, is similar to the results with RAND Health Insurance Experiment data (Deb and Trivedi, 2002), where the assignment was randomized to solve self-selectivity issues.

It should be noted that lowering the size of nominal coinsurance rate has a minor effect on the amount of total national health care expenditure in Japan. In 1997 nominal coinsurance rates were lifted for heads of households in the company managed insurance, yet, it did not result in the decrease of health care expenditure growth (Fig.3). The year 2000 saw an introduction of long-term care insurance. This scheme comprised long-term care cases, which were previously classified as general health care and therefore, reimbursed according to higher rates than those in the long-term care. The reform resulted in a sharp fall in health care expenditure growth: from 3% in 1999 to -2.7% in 2000. As for lifting of nominal coinsurance rates for heads of households in 2003, it did not lead to an immediate effect. At the same time lowering the fees for health care services in the unified fee schedule in 2002 and 2006 resulted in considerable falls in the rate of growth of health care expenditure.

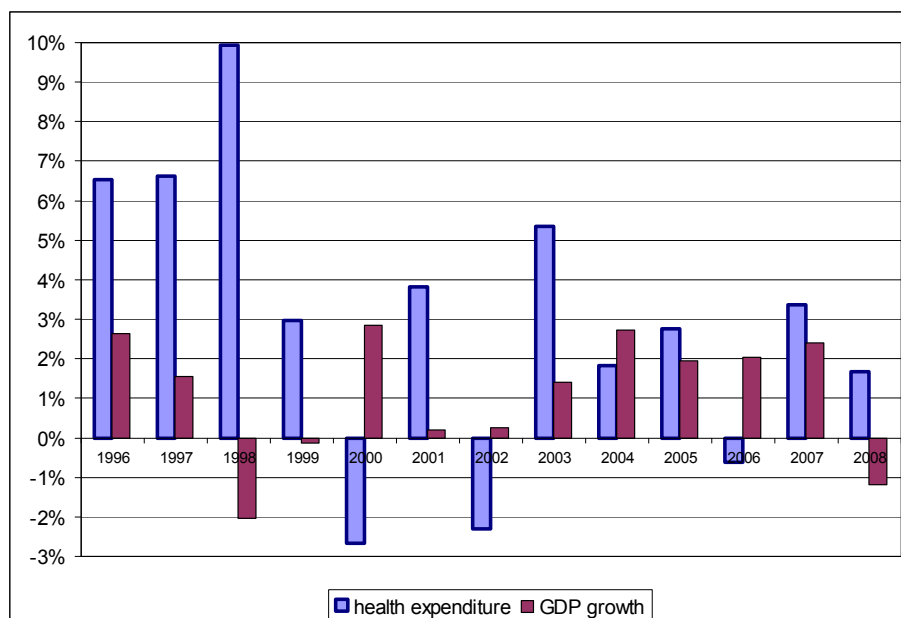


Figure 3. Rates of growth in Japanese national health care expenditure and GDP (in 2000 real terms)

Source: Calculations according to *Japan Statistical Yearbook*, 2012; 2011; 2010; 2009; 2005; 2002.

Notes: National health expenditure is calculated in 2000 real terms by adjusting for medical CPI.

³² However, our sample may not be comparable to the sample in Ii and Ohkusa (2002a), since the latter sample is people who had minor ailments.

Finally, Japan adheres to the principles of universal health insurance, relatively inexpensive to all citizens. Consequently, instruments apart from coinsurance rate are gaining importance in decreasing health care costs. One of such instruments is the prices in unified fee schedule. Since fee-for-service reimbursement leads to physician-induced demand, cost containment is traditionally implemented by changing prices for certain medical services and drugs within unified fee schedule. Yet, while lowering the general cost of drugs was usually enough to find sources for financing the increasing volume of medical services,³³ the revision of the year 2002 was the first to decrease the aggregate cost of medical services (Ikegami, 2006; Ikegami, 2005; Ikegami and Campbell, 2004). Accordingly, the fee for consequent consultations as well as the number of days with the basic charge in hospitals decreased (Nawata et al., 2006). The 2002 and 2006 revisions of unified fee schedule resulted in particularly noticeable decreases in the price for health care services. Indeed, in 2002 the fall in consumer price index (CPI) for health care was twice that of the CPI for all goods and services (in percentage points). In 2006 the CPI for all goods and services increased, while the CPI for health care went down. Accordingly, sharp falls in the rate of real health expenditure growth in 2002 and 2006 (Figure 3), might be explained by a decrease in the induced-demand due to lower prices in unified fee schedule.

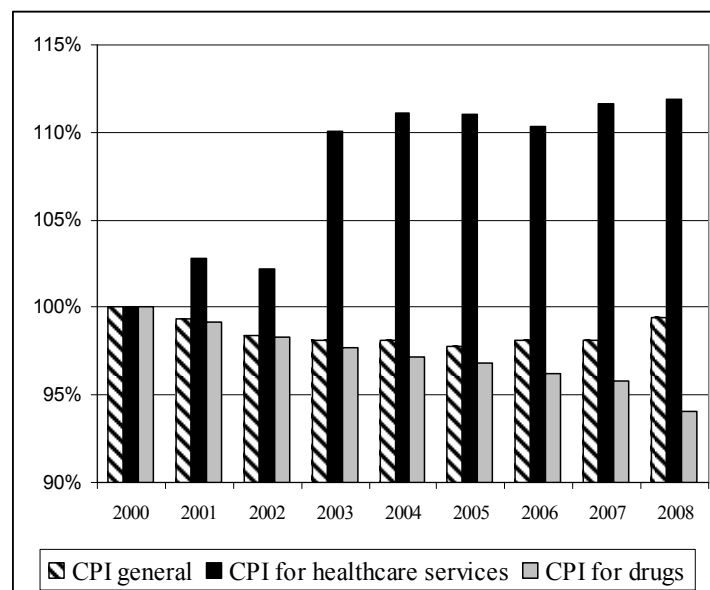


Figure 4. Consumer price indices in 2000-2008, percent (2000 is the base year)
Recalculations according to Japan Statistical Yearbooks (2010, 2007).

An introduction of inpatient prospective payment system in 2003 and a preparation for expanding prospective payment system to outpatient services may be regarded as another means to decrease physician-induced demand and enhance efficiency of health care providers.

³³ Note that while the cost of drugs in Japan is lower than in the US, the volume of drug consumption and the number of drug types per patient is extremely high (Ikegami, 1996b). The share of drug costs in the total structure of health care expenditure in Japan exceeds 30%, while the average value for other developed countries is in the range of 10-20%

7 Conclusion

The paper applies latent class models to account for unobservable individual heterogeneity in studying the effect of nominal coinsurance rate on consumer demand for health care. The analysis employs the 2000-2008 data of the Japanese Panel Survey of Consumers. The effect of nominal coinsurance rate is negative and significant. The estimations reveal that the April 2003 rise in coinsurance rate from 20% to 30% decreased the probability of having health care expenditure by 1.5%. The price elasticity of outpatient health care expenditure with respect to nominal coinsurance rate equals -0.5. As for the amount of health care expenditure and the average treatment effect of the reform, the effect of nominal coinsurance rate is stronger in the class of the frequent users of health care, who constitute 21% of individuals in the sample. Our finding with the latent class models with Japanese data, where the assignment of insurance plans is exogenous, is similar to the results with RAND Health Insurance Experiment data (Deb and Trivedi, 2002), where the assignment was randomized

Overall, the results confirm that coinsurance rate is an effective tool of cost containment terms of regulating consumer's decision to turn for health care. Yet, a number of other efficient mechanisms for containing the burden of health care costs have been recently implemented in Japan.

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(Yamauchi, 1999). This fact may be explained by induced demand, since about 60% of all drugs are dispensed directly by the doctor, who prescribed them (Ikegami, 2005).

Appendices

A Sampling in the Japanese Panel Survey of Consumers

The surveys are conducted from October 1 to October 31 each year. The data are collected and systematized by The Institute for Research on Household Economics. The respondents are cohorts A, B, C and D, constructed as follows. First, 47 prefectures are aggregated into 8 zones, according to the standard Japanese geographical classification: Hokkaido, Tohoku, Kanto, Chubu, Kinki, Chugoku, Shikoku, and Kyushu. Then the following division is implemented within each geographical zone:

- a) designated cities (with large population and certain features of prefectural governments);
- b) other cities;
- c) towns and villages (*chouson*).

Respondents of the first round of the survey (October 1993) were selected as a random sample from the population of each subgroup of cities, towns, and villages (*a*, *b*, and *c*)³⁴ in each geographical zone with regard to the following two characteristics: age and marital status. The constructed cohort A consisted of 1,500 women aged 24-34 (as of March 1992). The comparison of cohort A with the national data demonstrated that the share of unmarried women was slightly below the national average. Therefore, an additional sample of 500 women (cohort B) was constructed in 1997. Similarly to cohort A, the respondents in cohort B were a random sample from the population of the three subgroups of cities, town, and villages in each geographical zone. The age of respondents in cohort B was kept in the range of 24-27 (as of March 1996). Cohort B is constructed so that the ratios of married – unmarried and living in a household – unmarried and living alone women were 3 to 3 to 5.

Finally, as with each consequent round of the longitudinal survey the number of respondents kept shrinking due to migration and other reasons, additional samples of 836 women (cohort C) and 636 women (cohort D) were created in 2003 and 2008, respectively. The following adjustments of the sampling procedure are conducted in constructing cohorts C and D. First, the number of designated cities increased from 13 in 1993 to 14 in 2003, and to 18 in 2008. Second, the ratios of married – unmarried and living in their household – unmarried and living alone women were 3 to 4 to 7 in cohorts C and D. Cohort C are women aged 24-29 as of March 2003, and cohort D are women aged 24-28 as of March 2008.

³⁴ There are no designated cities in Shikoku, so respondents were selected from locations in the two subgroups: *b* and *c*.

B Deviance residuals and Anscombe 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

$$r_D = \text{sign}(y_i - \hat{\mu}_i) \sqrt{d_i},$$

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 Weibull 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:

$$\ln L_i(\mu_i) = \ln P + P \ln \Gamma\left(\frac{P+1}{P}\right) - P \ln \mu_i + (P-1) \ln y_i - \left[\frac{y_i}{\mu_i} \Gamma\left(\frac{P+1}{P}\right)\right]^P, \quad (\text{B1})$$

where P is the scale parameter and $\Gamma(\cdot)$ denotes gamma function.

Since only i -th component of the sum $\ln L$ depends on μ_i , the maximization of $\ln L$ is equivalent to solving the following maximization problems for each $\ln L_i(\mu_i)$:

$$\ln L_i(\mu_i) \rightarrow \max_{\mu_i} \quad (\text{B2})$$

Differentiating (B1) with respect to μ_i , we obtain the first order conditions

$$-\frac{P}{\mu_i} - P \left[\frac{y_i}{\mu_i} \Gamma\left(\frac{P+1}{P}\right) \right]^P \mu_i^{-1-P} = 0, \quad (\text{B3})$$

$$\text{with the solution } \mu_i^* = \Gamma\left(\frac{P+1}{P}\right) \cdot y_i \quad (\text{B4})$$

Plugging μ_i^* in (B1) yields:

$$\ln L_i(\mu_i^*) = \ln\left(\frac{P}{y_i}\right) - 1 \quad (\text{B5})$$

$$\text{By definition, } d_i = 2 \cdot (\ln L_i(\mu_i^*) - \ln L_i(\hat{\mu}_i)). \quad (\text{B6})$$

Plugging $\hat{\mu}_i$ in (B1) we obtain $\ln L_i(\hat{\mu}_i)$, and then rewrite (B6) as

$$d_i = 2 \left(-P \ln\left(\frac{y_i}{\hat{\mu}_i}\right) - 1 - p \ln \Gamma\left(\frac{P+1}{P}\right) + \left[\frac{y_i}{\hat{\mu}_i} \Gamma\left(\frac{P+1}{P}\right) \right]^P \right). \quad (\text{B7})$$

$$\text{Finally, } r_{Di} = \text{sign}(y_i - \hat{\mu}_i) \cdot \sqrt{2 \left(-P \ln \left(\frac{y_i}{\hat{\mu}_i} \right) - 1 - p \ln \Gamma \left(\frac{P+1}{P} \right) + \left[\frac{y_i}{\hat{\mu}_i} \Gamma \left(\frac{P+1}{P} \right) \right]^P \right)}. \quad (\text{B8})$$

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:

$$r_{Ai} = \frac{A(y_i) - A(\mu_i)}{A'(\mu_i) \sqrt{V(\mu_i)}} \quad (\text{B9})$$

$$A(\cdot) = \int_{-\infty}^t \frac{dt}{V^{1/3}(t)}, \quad (\text{B10})$$

where i denotes the index for observation, y_i is the dependent variable, μ_i stands for the conditional mean $E(y_i|\mathbf{x}_i)$, and $V(\cdot)$ is variance function for μ_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 (B9)-(B10) reveals that the scale parameters of the distributions are neglected in McCullagh's and Nelder's formulas for $V(\cdot)$. Therefore, our application of (B9)-(B10) for

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

The panel data generalized linear model with exponential distribution family (a special case of Weibull distribution family with the scale parameter equal to unity) provides the best goodness of fit in terms of mean squared error, mean absolute prediction error and raw bias. Although the skewness/kurtosis test rejects the null hypothesis of normality of standardized deviance residuals and Anscombe residuals in the model with latent classes, the distribution of the residuals is close to normal (Fig.B1-B2).

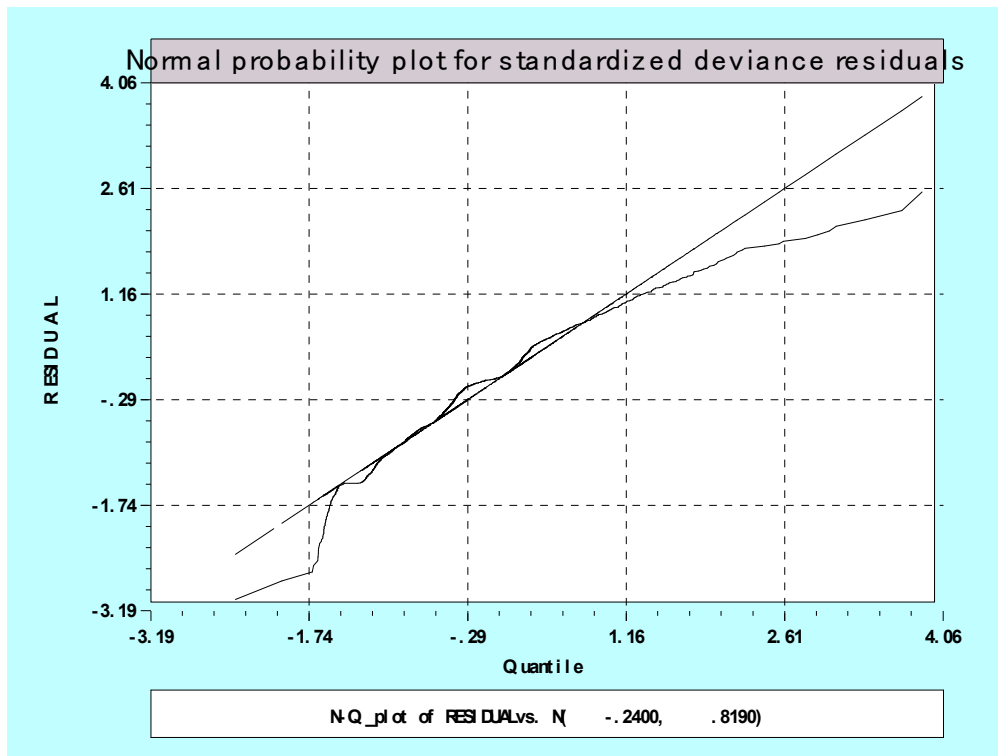


Figure B1. Quintiles of standardized deviance residuals versus quintiles of normal distribution for the panel data generalized linear model with latent classes and exponential distribution family

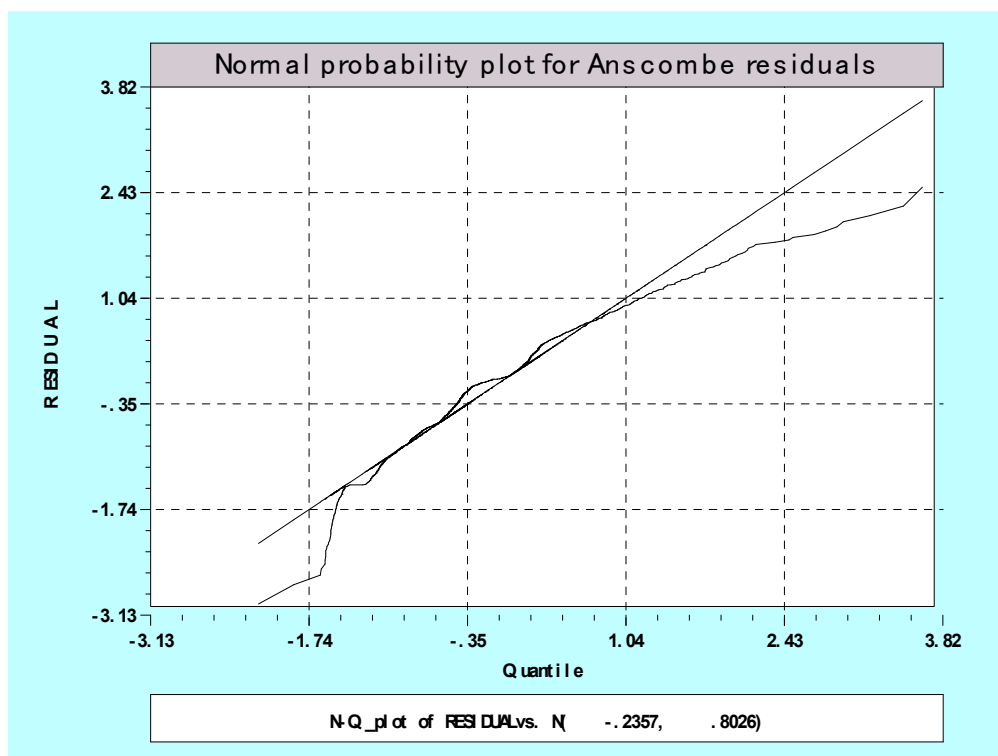


Figure B1. Quintiles of Anscombe residuals versus quintiles of normal distribution for the panel data generalized linear model with latent classes and exponential distribution family

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