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Heterogeneous effect of coinsurance rate on healthcare costs: generalized finite mixtures and matching estimators

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Abstract

The paper proposes a combination of finite mixture models and matching estimators to account for heterogeneous and nonlinear effects of the coinsurance rate on healthcare expenditure. We use loglinear model and generalized linear models with different distribution families, and measure the conditional average treatment effect of a rise in the coinsurance rate in each component of the model. The estimations with panel data for adult Japanese consumers in 2008-2010 and for female consumers in 2000-2010 demonstrate the presence of subpopulations with high, medium and low healthcare expenditure, and subpopulation membership is explained by lifestyle variables. Generalized linear models provide adequate fit compared to loglinear model. Conditional average treatment effect estimations reveal the existence of nonlinear effects of the coinsurance rate in the subpopulation with high expenditure.

JEL Classification Codes: C440, C610, I130

Keywords: finite mixture model; generalized linear model; matching estimators

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1 Introduction

Discussions of coinsurance in the health economics literature were initially related to issues of moral hazard in the demand for healthcare, but coinsurance rates have been shown to impact the intensity of medical treatment, and regulatory economics use coinsurance rates or other forms of copayments as an instrument for containing supplier-induced demand in a fee-for-service reimbursement environment. Consistent with the predictions of theoretical models, empirical evidence often demonstrates a negative relationship between the coinsurance rate and the scale of healthcare expenditure. However, measurement of the average effect for the whole pool of consumers may conceal issues of price-inelastic healthcare expenditure for certain subgroups. So disentangling variation in consumer response to the coinsurance rate can be viewed as integral to judgments about the efficiency of health insurance policies and welfare issues of insurance coverage.

The paper proposes a combination of finite mixture models and matching estimators to account for unobservable consumer heterogeneity and nonlinear effects of the coinsurance rate on healthcare expenditure. We use finite mixture generalized linear models with different distribution families, and measure the conditional average treatment effect of a rise in the coinsurance rate in each component of the model. The methodology is applied to an assessment of the most recent increase of coinsurance rates for a number of Japanese consumers, exploiting a unique combination of the longitudinal data of the Japanese Panel Survey of Consumers (2000-2010) and the Japan Household Panel Survey (2008-2010).

The novelty of the present paper is threefold. Firstly, the paper measures healthcare expenditure with finite mixture generalized linear models and analyzes goodness of fit through in-sample and out-of-sample crossvalidation. Secondly, the paper applies conditional average treatment effect (CATE) estimators (Abadie and Imbens (2011)) to the finite mixture model, modifying subpopulation approach of Hirano et al. (2000). Namely, we compute individual estimates through weighting component-specific CATEs by posterior probability of component membership. Finally, the paper offers an evaluation of a natural experiment in terms of heterogeneous price effect for healthcare expenditure.

The estimations with finite mixture panel data models demonstrate that both loglinear model and generalized linear model with a Weibull distribution family provide adequate fit for healthcare expenditure. The effect of the coinsurance rate is negative and heterogeneous. Marginal effect and coefficients of treatment effect in difference-in-difference estimations are larger in absolute terms in the components with higher healthcare expenditures. Estimates of conditional average treatment effect with matching and regression reveal the presence of nonlinear effects of the coinsurance rate in component with high healthcare expenditure.

The major limitation of our analysis is the fact that the data on healthcare expenditures and price variable in Japan Panel Survey of Consumers are available for the sample of women aged 24–51. We assess the internal validity of our analysis with finite mixture generalized linear models, applying the same methodological framework to the representative panel data on adult Japanese consumers in Japan Household Panel Survey. As regards external validity of the values of the estimates, we note that finite mixture models may be applied separately to men and women or to a particular age cohort and discuss the issues related to the age and sex bias.

The remainder of the paper is structured as follows. Section 2 overviews methodological background. Section 3 describes Japanese social health insurance system and the natural experiment, evaluated in the analysis. Section 4 sets up empirical framework with a combination of finite mixture models and matching estimators. Section 5 describes the data and variables. The findings of the empirical analysis are summarized in section 6. Section 7 discusses implications of the results, and Section 8 concludes the paper. Details about datasets and imputations are presented in the Appendices.

2 Methodological background

Studies of the heterogeneity of the coinsurance rate or similar price effects (e.g., deductibles, add-ons, supplementary insurance, or drug coverage) on healthcare demand generally relate to observational studies, choice experiments or social experiments. However, observational studies and social experiments are likely to suffer from potential selection biases. Also, experimental analyses require extremely careful design to ensure the generalizability of their results and they have the disadvantage of lacking pre-reform data (De Bekker-Grob et al. (2012); Levitt and List (2007); Welch et al. (1987)). Natural experiments, on the other hand, make it possible to apply policy evaluation methods to raise the accuracy of the estimates and incorporate potential nonlinear price effects, which are forecasted in the theoretical literature (Westerhout and Folmer (2013)). While the former issue is addressed with difference-in-difference estimators, the nonlinearity is to the best of our knowledge confronted only Winkelmann (2006) who employs quintile regressions and by Barros et al. (2008) through an application of Abadie et al.'s (2004) matching estimators.

However, the analyses in Barros et al. (2008) and Winkelmann (2006) stem from the theoretical framework modeling treatment of a separate episode of illness, when the identification condition and hence the adequate fit of multi-part models is the presence of data on actual illness episodes.[1] Yet, consumer surveys often suffer from the absence of data on illness spells, and the empirical literature proposes to model healthcare utilization as a mixture of distributions for zero and non-zero use (Deb and Trivedi (1997)). More formally, such consumer characteristics as health status, attitude to health risk and lifestyle influence the membership

[1]Indeed, an illness episode, which encompasses various services offered over a period of time to provide the best cure for a particular medical problem, may be regarded as a natural unit for the analysis of healthcare demand (Keeler and Rolph (1988); Hornbrook et al. (1985)).

in unobserved (latent) classes (Deb and Trivedi (2002); Wedel and DeSarbo (2002)). The justification for mixture models comes from the inability to fully capture the consumer characteristics related to the behavioral pattern of healthcare consumption using self-assessed health and other measurable variables. The use of a *finite* number of components is based on theoretical expectations about a small number of groups with high and low demand for healthcare and on formal arguments about the requirements for convergence of the estimation algorithms (especially in case of a multimodal distribution) along with an overall good approximation of a continuous mixing distribution by a finite number of points of support (Cameron and Trivedi (2013); Greene (2007)). When data are likely to violate the assumption about a single illness spell, latent class models outperform multi-part models in fitting consumer demand, particularly in the tails of the distribution (Santos Silva and Windmeijer (2001); Deb and Holmes (2000)).

It is plausible to assume that the price variable may impact the demand for healthcare in a way, which is specific to each latent class. In this context Munkin and Trivedi (2010), which measures average treatment effect of additional drug coverage in each latent class, is, to the best of our knowledge, the only paper combining finite mixture models with estimations of treatment effects. But measuring the local average treatment effect relies on particular instruments, and a combination of finite mixture models with policy evaluation methods, which do not relate to any functional form (e.g., matching estimators), would offer more flexible estimates. As regards panel data finite mixture models of healthcare expenditure, experimental literature demonstrates the superiority of generalized linear mixture models over loglinear models (Jones et al. (2013), Baldi et al. (2013); Deb and Burgess (2003)). However, the real data estimates with finite mixture models for healthcare expenditure have so far been limited to linear models with a logged dependent variable and Duan's (1983) smearing retransformation. But the approach may only be applicable in case of normality or homoscedasticity of errors, while generalized linear models, which have the advantage of improved precision and robustness of the estimate of the conditional mean, would be a solution to the retransformation problem and might be applied to finite mixture estimations (Greene (2007); Manning and Mullahy (2001)).

Our paper focuses on a natural experiment in Japan. The coinsurance rate in Japan has been shown to have negative impact on healthcare demand for the whole population of consumers, but analyses with Japanese data are commonly limited to observational studies (Bessho and Ohkusa (2006); Ii and Ohkusa (2002a), Ii and Ohkusa (2002b); Yamada (1997); Bhattacharya et al. (1995)). Moreover, many papers use data at prefectural or insurance association level, which might lead to inaccuracy due to aggregation (Babazono et al. (2003); Sawano (2001); Kupor et al. (1995); Nishimura (1987); Senoo (1985); Maeda (1978); Newhouse et al. (1980)). As for evaluating natural experiments, the general pattern in study of the behavior of Japanese consumers who have experienced a change of coinsurance rates provides only limited assessment of the effect. Moreover, such analyses with data for a certain company or for patients with certain illnesses in a certain company may suffer from selection bias due to sample-specific individual characteristics (Babazono et al. (2005); Tokita et al. (2002)). Kan and Suzuki (2010) attempt to employ program evaluation methods in case of a natural experiment. Nonetheless, the treatment group (heads of households) and the control group (dependents) in their approach are not fully comparable since they are likely to differ in age and sex.[2] Shigeoka (2014) uses a regression discontinuity approach to address the effect of consumer enrollment in insurance for the elderly, but the analysis does not focus on potential heterogeneity of the coinsurance rate.

3 The Japanese social health insurance system

3.1 Overview

Since 1961 Japan has had a mandatory and universal social health insurance, which has resulted in the expansion of healthcare utilization and improvement of the population's health status (Kondo and Shigeoka (2013); Ikegami et al. (2011)). Enrollment in one of the mutually exclusive health insurance plans is obligatory and depends on an 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 the self-employed, retirees and their dependents; 2) government-managed insurance for employees of small firms and their dependents; 3) company-managed insurance associations created by firms with over 300 workers for their employees and employees' dependents; 4) benefit schemes set up by mutual aid associations (Table 1).

INSERT Table 1 HERE

The medical services and drugs covered by health insurance and their costs are listed in the national fee schedule, which is revised biennially by the Ministry of Health, Labor, and Welfare (MHLW) following the recommendations of its advisory committee – the Central Social Insurance Medical Council (Ministry of Health, Labor and Welfare (2013b); Ikegami (2006); Campbell and Ikegami (1998)).[3] The schedule includes four parts: medical services; dental services; drugs and materials; and prospective fees for inpatient care (a part of the schedule since 2003, when a prospective payment system began to be voluntarily employed by

[2] Dependents in company-managed insurance commonly include housewives and non-working children.

[3] The predecessor of the current fee schedule is the schedule developed for office based physicians upon the introduction of health insurance for manual workers in 1927 (Campbell and Ikegami (1998)). The 1961 adoption of the universal health insurance retained the coexistence of the old fee schedule, favoring private practitioners and exploited by clinics and small hospitals, and the new schedule, supporting specialized care and used by hospitals (National Institute of Population and Social Security Research (2005); Campbell and Ikegami (1998); Ikegami (1991)). Additionally, an establishment of a separate health insurance for the elderly in 1982 led to an adoption of a special fee schedule for financing the treatment of this age cohort (National Institute of Population and Social Security Research (2005); Ikegami (1991)). The three schedules are set by the MHLW, and the differences between the three schedules are minor (Ikegami, 1991). The old and new schedules were combined in 1994, and therefore, currently, a unified national fee schedule applies to all healthcare providers (Ikegami et al. (2011)).

hospitals). Each item in the schedule is given a certain number of points, where a point is equivalent to 10 yen (Ministry of Health, Labor and Welfare (2012b)).[4] With a few exceptions (larger outpatient consultation fees for physicians in clinics than in hospitals; large fees for home visits; hospital admission fee depending on nurse staffing ratio) the schedule is unified and does not differentiate costs between providers.[5]

Japanese social health insurance is based on free access. The users of any health insurance plan can choose any healthcare institution, regardless of its location or type (e.g., private/public, hospital, clinic or ambulatory division of hospital). There are no gatekeepers, and payments for seeking the services of a large facility without referral are negligible (Ikegami and Campbell (1995)).

3.2 The coinsurance rate

As well as regulating supplier-induced demand by means of prices in the national fee schedule,[6] Japan also regards the level of the coinsurance rate as an important instrument for cost containment. The coinsurance rate for each health insurance plan is determined by the Health Insurance Law. When national health insurance became universal in 1961, the coinsurance rate within this system was set at 50%. It was lowered to 30% for heads of households in 1963 and for dependents in 1968. The policy of enhancing healthcare accessibility also led to a reduction of the 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 schemes owing to special social guarantees to "salary men" during the country's growth boom in the 1960s-1970s. But soaring healthcare costs and decelerating growth of labor force in the late 1970s and early 1980s led to the introduction of a 10% coinsurance rate in 1984 for heads of households in company-managed insurance schemes. Later, in September 1997, the coinsurance rate for heads of households in company-managed insurance, government-managed insurance, seamen's insurance and mutual-aid benefit schemes went up to 20%. Moreover, all health insurance plans saw the introduction

[4] A point represented an average cost of daily drug dose in the first schedule of 1927, and became equivalent to 10 yen in 1961 (Campbell and Ikegami (1998)). It may be noted that till the end of the 19th century the Japanese doctors practicing traditional medicine formally offered their services for free, asking reimbursement only for the cost of medicines used in the course of treatment (Campbell and Ikegami (1998)).

[5] Neither health insurance society nor healthcare provider may negotiate fees besides the national schedule (Ikegami (1991)). Moreover, 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.

[6] The process resembles muddling through the items (Ikegami and Campbell (1995)), yet it proves an effective instrument for cost containment and volume control: first, the size of the aggregate increase in the costs of medical services and drugs is decided, and then the price of each item is altered individually (Ikegami (1991)). For example, in the 1980s-1990s the schedule implemented bundling of fees to reduce the price of laboratory tests (Ikegami and Campbell (1995)); raised the fee for pediatric consultation since the number of patients decreased (Ikegami and Campbell, 1999). Moreover, some fees (e.g. for surgery) may be set below costs, so that such procedures could be provided mainly in public medical facilities, which receive subsidies (Arai and Ikegami (1998)). Overall, the purpose of the schedule is to restrict expensive services and favor low cost items (Ikegami and Campbell (1995)). It may be noted that while lowering the general cost of drugs used to be sufficient for financing the increasing volume of medical services, the 2002 revision of unified fee schedule 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)).

of out-of-pocket lump-sum payments for prescriptions with multiple drugs and a rise in coinsurance for the elderly from 10% to 20%.

3.3 Natural experiment of 2003

In April 2003 the coinsurance rate for outpatient healthcare, drugs and inpatient healthcare for heads of households in company-managed insurance, government-managed insurance, seamen's insurance and mutual-aid benefit schemes was increased from 20% to 30% (Table 2). Also, the coinsurance rate for dependents in these schemes was raised from 20% to 30%, establishing a uniform 30% coinsurance rate for the nonelderly adult population. In order to maintain the concept of affordable healthcare, the Diet accompanied the 2003 rise by a ban on any further increases of the coinsurance rate (Ikegami (2006)).

INSERT Table 2 HERE

4 Empirical models

Following the classic theoretical framework and empirical models of healthcare expenditure, we consider a vector $\mathbf{x}$ of the following basic covariates, related to individual's demand for healthcare: the coinsurance rate, individual's health status, age, education, residence, and household income.[7] By including the coinsurance rate in the list of $\mathbf{x}$ we assume that the rate is exogenous. It may be noted that the health insurance plan used by an individual in Japan may be regarded as synonymous to his or her position in the labor market. So there is potential for endogeneity of coinsurance rates: individuals with higher demand for healthcare might prefer to work in a company (where coinsurance rates are lower) as opposed to becoming dependents or being self-employed. However, this is unlikely to apply to young women, who constitute our sample, for a number of reasons: firstly, the literature on job market searches by new graduates in Japan does not report any selection according to health status; secondly, severely ill consumers (those who required hospitalization due to a serious illness or depression) are excluded from our sample; thirdly, change of jobs is not yet as widespread in Japan as in other developed countries, and does not commonly occur among young people; and fourthly (and most importantly), our sample consists women, who have a weak attachment to the labor market (Hashimoto (1990)).

In the present paper we focus exclusively on outpatient care, which is provided in Japan via outpatient facilities (clinics without beds or with up to 19 beds) or outpatient departments of hospitals (hospitals are

[7] As for risky behaviors (smoking, drinking), index of phycological distress or weight, such questions are present only in the last one-three round(s) of questionnaire and therefore can not be used for the analysis of pre-reform and post-reform data. Family size is excluded since it represents primarily adult family members in the sample of unmarried women without children. Therefore, family size is strongly correlated with household income.

facilities with over 20 beds). The focus on outpatient care is explained by our desire to use dependents in non-national health insurance plans as a control group, which required that we ignore simultaneous rise in the coinsurance rate for inpatient care of dependents. Moreover, the treatment group (heads of households in non-national health insurance plans) experienced a rise in the coinsurance rate for both inpatient and outpatient care. Consequently, our approach does not enable analysis of a potential substitution effect between inpatient and outpatient care. In theory, since inpatient care is more expensive (in terms of overall cost), the reform which increases prices for both types of care might induce an increase in utilization of outpatient care. But the inpatient and outpatient care may be regarded as extremely distinct for young Japanese individuals (who constitute both the treatment and the control group in our paper). Indeed, there is a general aversion towards invasive procedures in Japan, so that unjustified hospitalizations occur primarily among the elderly.

Finally, owing to the system of benefits to make high-cost medical care more affordable, the actual share of out-of-pocket expenditure incurred by an enrollee (often called the effective coinsurance rate) is lower than the nominal coinsurance rate (Ikegami and Campbell (1999)). But the various benefits and exemptions mostly relate to inpatient care (Shigeoka (2014)), as outpatient care rarely reaches the stop-loss level. Indeed, using data from the Japan Household Panel Survey we estimate that only 2.9% (9.5%) of respondents, who have characteristics similar to our sample and did not seek inpatient care, applied for medical care benefits (medical expenditure deduction). Consequently, in this paper we follow the literature, which uses the nominal coinsurance rate as the price of outpatient care in Japan (Bessho and Ohkusa (2006); Babazono et al. (2003); Ii and Ohkusa (2002a)).

Healthcare expenditure in our analysis is unified fee schedule points (Kan and Suzuki (2010); Kan and Suzuki (2006); Babazono et al. (2005); Tokita et al. (2002); Maeda (1978)), i.e. the overall cost of healthcare borne by the insured and by the health insurance society. The approach is common in the Japanese health economics literature as it reflects physician behavior as the agent of a consumer.[8] We account for the potential effect of the changes in the national fee schedule through adjusting unified fee schedule points by annual inflation of medical goods, services and grugs, covered by health insurance. As regards annual inflation of medical goods and services, *not* covered by health insurance, we use it as covariate in estimating the share of non-insurance healthcare expenditure in the auxiliary sample of Japan Household Panel Survey. The variable, however, proves insignificant and is not exploited in the imputations (see Appendices B-C for details).

This paper concentrates on positive healthcare expenditure, estimating it independent of binary choice

[8]As robustness check, we conduct our estimations with consumer out-of-pocket expenditure and obtain quantitatively similar results.

equation for seeking healthcare. The approach corresponds to theoretical arguments about affordability of healthcare in Japan and the strong degree of trust between physician and patient (Muramatsu and Liang (1996)). Moreover, our formal attempt for joint estimation of the binary choice model and the model for healthcare expenditure showed that it did not fit our data.

4.1 Panel data finite mixture models

For each observation $i = 1, ..., N$ the dependent variable y_{it} is observed over time periods $t = 1, ..., T$. The observations are drawn from the mixture of C unobserved subpopulations (components) in unknown proportions $\pi_j > 0$, $j = 1, ..., C$ (prior probabilities of component membership), so that $\sum_{j=1}^{C} \pi_j = 1$. The unconditional probability density of the dependent variable is the sum of conditional probability densities: $f(y_i|\pi, \boldsymbol{\theta}) = \sum_{j=1}^{C} \pi_j f(y_i|\boldsymbol{\theta}_j)$, where $\boldsymbol{\theta}_j$ is the vector of unknown parameters. Under the assumption of independent repeated measurements of y_{it} over time, the joint density of y_{it} for the T repeated observations is the product of the marginal densities in each period: $f_j(y_i|\boldsymbol{\theta}) = \prod_{t=1}^{T} f_j(y_{it}|\boldsymbol{\theta}_{jt})$, where marginal densities in the period with missing data are replaced by unity (Greene (2007); Wedel and DeSarbo (2002)). In case of a short panel each observation is assumed to reside in the same component over the whole period of time,[9] so

$$f(y_{it}|\pi, \boldsymbol{\theta}) = \sum_{j=1}^{C} \pi_j \prod_{t=1}^{T} f(y_{it}|\boldsymbol{\theta}_j) \tag{1}$$

Finally, Bayes theorem gives the estimate of the posterior joint probability of belonging to component j:

$$P(i \in j) = \pi_{ij} \cdot \prod_{t=1}^{T} f(y_{it}|\mathbf{x}_{it}, \boldsymbol{\theta}_j) \Big/ \sum_{j=1}^{C} \pi_{ij} \cdot \prod_{t=1}^{T} f(y_{it}|\mathbf{x}_{it}, \boldsymbol{\theta}_j) \tag{2}$$

Based on $\max\{P(i \in j)|j = 1, ..., C\}$, the most probable component for each i may be determined.[10]

Along with the interpretation of components (latent classes) as behaviorally different, we mention the argument about a better approximation of the underlying unknown distribution using a finite mixture model. Note that the model imposes an implicit constraint through which the classes may be ordered, e.g. in case of a two-component model: $Ey_1 > Ey_2$, where index 1 stands for frequent users with higher expenditure (component 1) and index 2 denotes infrequent users with lower expenditure (component 2).

[9] An alternative approach, based on Markov process assumptions about transition between components over time commonly applies to long panels and may fail to provide component-specific estimates (Wouterse et al. (2013); Collins and Lanza (2010)).

[10] Taking a weighted average of the fitted values for the dependent variable for each observation in all latent classes (Greene (2005)) does not enable contrasting behavior of individuals from subpopulations.

4.1.1 Loglinear model for positive healthcare expenditure

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

$$\log\, y_{it} = \mathbf{x}'_{it}\boldsymbol{\gamma}_j + \zeta_{it} + \nu_i$$

$$E\nu_i = 0; E\zeta_{it} = 0; \zeta_{it} \text{ and } \nu_i \text{ are non-correlated; } \zeta_{it} \text{ and } \mathbf{x}_{it} \text{ are non-correlated} \tag{3}$$

where y_{it} is healthcare expenditure, $\mathbf{x}_{it}$ are covariates related to the demand for healthcare, γ_j are coefficients for j-th component.

4.1.2 Generalized linear models

Owing to the retransformation problem in regressions with a logged dependent variable (Duan (1983)), estimating loglinear model (3) 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);Mullahy (1998)). Although there are other possible solutions,[11] the advantages of generalized linear models are improved precision and robustness of the estimate of the conditional mean (Manning and Mullahy (2001)). As regards finite mixture generalized linear model, it assumes that

$$f(E(y_{it}|\mathbf{x}_{it}, j)) = \mathbf{x}'_{it}\boldsymbol{\delta}_j, \text{and } (y|\mathbf{x}_{it}, j) \sim g(y_{it}, \mathbf{x}_{it}, \boldsymbol{\theta}_j), \tag{4}$$

where f is a link function, g is a family of distribution, $\boldsymbol{\delta}_j$ are coefficients, $\boldsymbol{\theta}_j$ are ancillary parameters for j-th component (Greene (2007); Wedel and DeSarbo (2002)). We use LIMDEP 9.0 to analyze loglinear finite mixture models and the models with gamma, Weibull, and inverse Gaussian families. As the estimations exploit maximum likelihood algorithms, we use different sets of starting values to avoid local optima (Cameron and Trivedi (2013)).

4.2 Treatment effect

The treatment group consists of respondents who experienced a rise of the coinsurance rate due to the 2003 reform: heads of households in company-managed insurance, government-managed insurance, seamen's insurance, and benefit schemes of mutual aid associations. The control group are enrollees in national health insurance, and dependents in other health insurance plans. The control group is constructed to match the

[11] Alternative ways include 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 (Mihaylova et al. (2011), Mullahy (2009), Basu and Manning (2009)).

treatment group as regards the major correlates of the demand for healthcare: household income, age, sex, state of health, education and residence (Deb and Trivedi (2013); Bago D'Uva and Jones (2009); Deb and Holmes (2000)). It should be noted that the variables are not affected by the treatment, which is a necessary identification condition for the analysis (Angrist and Pischke (2009)).

In case of the loglinear model, where the hypothesis of homoskedasticity of errors is not rejected with our sample, we use smearing retransformation to estimate the fitted value of healthcare expenditure $\hat{y}_{jit}^{loglinear}$:

$$\hat{y}_{jit}^{loglinear} = E(y_{it}|\mathbf{x}_{it}, \boldsymbol{\theta}_j) = exp(\mathbf{x}_{it}'\hat{\boldsymbol{\beta}}_j) \cdot \frac{1}{N}\sum_{i=1}^{N} exp(\log\, y_{it} - \mathbf{x}'\hat{\boldsymbol{\beta}}_j), \tag{5}$$

where N is the size of the whole sample and $j = 1, ..., J$. In the generalized linear model with Weibull distribution family (which provides the best fit among other generalized linear models) the fitted value $\hat{y}_{jit}^{glm}$ is measured as

$$\hat{y}_{jit}^{glm} = E(y_{it}|\mathbf{x}_{it}, \boldsymbol{\theta}_j) = exp(-\mathbf{x}_{it}\hat{\boldsymbol{\gamma}}_j)^{-\frac{1}{p_j}} \cdot \Gamma(1 + \frac{1}{p_j}), \tag{6}$$

where Γ denotes gamma function and p_j is the shape parameter in the Weibull distribution for the j-th component.

We follow Dafny and Dranove (2006) and study the difference between the mean values of the outcomes $E(y_{it}|\mathbf{x}_{it}, \theta_j)$ for the post-reform years (2003-2010) and the pre-reform years (2000-2002):

$$d_{ij}^{model} = \frac{1}{S_1}\sum_{s=1}^{S_1} \hat{y}_{2002+s}^{model} - \frac{1}{S_2}\sum_{s=1}^{S_2} \hat{y}_{1999+s}^{model}, \tag{7}$$

where *model* is loglinear or GLM with Weibull distribution family. According to Bertrand et al. (2004), such collapsing of the data into pre-reform and post-reform periods is a solution to inconsistency of standard errors of the coefficient for the average treatment effect. The lengths of the pre-reform and post-reform periods ($S_1 = 8$, $S_2 = 3$) are explained by data availability. Estimations with shorter post-reform periods lead to results, which are similar to the findings with the longest post-reform period available.

4.2.1 Average treatment effect

The sample average treatment effect $\bar{\tau}$ is

$$\bar{\tau} = \frac{1}{N}\sum_{i=1}^{N} E[y_i(w_i = 1) - y_i(w_i = 0)], \tag{8}$$

where $i = 1, ..., N$ indicates individuals, y_i is the outcome, w_i is the treatment indicator which equals one under the active treatment (i.e. the rise in nominal coinsurance rate) and zero under the control.

The component-specific average treatment effect $\bar{\tau}_j$ in the framework of finite mixture models and difference-in-difference estimations becomes:

$$\bar{\tau}_j = \frac{1}{N}\sum_{i=1}^{N} E[d_{ij}(w_i = 1) - d_{ij}(w_i = 0)|\boldsymbol{\theta}_j], \tag{9}$$

where j is the index of component, $i = 1, ..., N$ indicates individuals and d_{ij} is measured in the corresponding model. Component-specific ATE is estimated under the assumption that all observations belong to component j.

Hirano et al. (2000) introduce a natural definition of ATE $\bar{\tau}_g$ for subpopulations, formed with a weighting function $g(\cdot)$ as:

$$\bar{\tau}_g = \sum_{i=1} g(x_i)\tau_i \Big/ \sum_{i=1} g(x_i) \tag{10}$$

where τ_i is ATE measured with estimations for the whole sample.

In case of finite mixture models the weighting function $g(\cdot)$ is posterior probability of component membership $g(x_i, j) = P(i \in j)$, and the sum of posterior probabilities equals unity. So the definition of $\bar{\tau}_j^{ATE}$ for each component becomes:

$$\bar{\tau}_j^{ATE} = \frac{1}{N_j}\sum_{i=1}^{N_j}\sum_{j=1}^{C} P(i \in j)E[d_{ij}(w_i = 1) - d_{ij}(w_i = 0)|\boldsymbol{\theta}_j], \tag{11}$$

where $i = 1, ..., N_j$ indicates individuals in component j.

In other words, first we measure component-specific ATE. Then, for each observation we weight these component-specific ATEs by posterior probability of component membership $P(i \in j)$, and take average over the sample size N_j of each component.

4.2.2 Linear estimator conditional on covariates

First we obtain component-specific estimates. For each j we run a linear regression:

$$d_{ij} = \tau_j w_i + \boldsymbol{\kappa}'_{ij}\mathbf{h}_i^{pre} + \psi_i, E\psi_i = 0, \tag{12}$$

where $\mathbf{h}^{pre}$ denotes the average values of covariates $\mathbf{x}$ (excluding price) in the pre-reform years, and the fitted value of τ_j give the linear estimate of the component-specific conditional average treatment effect. Then we weight the estimates by $P(i \in j)$ and average over sample size of each component.

4.2.3 Nonlinear conditional estimator in matching and regression

While a number of methods measuring average treatment effect for non-randomized treatment assignment exist in the literature, 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)). To estimate average treatment effect, conditional on the sample distribution of covariates (CATE), in a finite mixture model we average over sample and posterior distribution of covariates:

$$\overline{\tau(\mathbf{x})}_j^{CATE} = \frac{1}{N_j} \sum_{i=1}^{N_j} \sum_{j=1}^{C} P(i \in j) \Big(E[d_{ij}(w_i = 1) - d_{ij}(w_i = 0) | \mathbf{h}_i^{pre}, \boldsymbol{\theta}_j] \Big) \tag{13}$$

Using the STATA module *nnmatch* (Abadie et al. (2004)) we correct for the asymptotic variance of matching estimators by matching and regression, and guarantee that $0 < Prob(w = 1|\mathbf{h}^{pre}) < 1$ (nonoverlap assumption). The second identifying assumption (unconfoundedness) is the premise that conditional on a given set of covariates $\mathbf{h}^{pre}$ participation in the reform is independent from the outcome in both states: participation and nonparticipation (Rosenbaum and Rubin (1983)). A justification for the assumption stems from the age-demographic structure of individuals in our sample: firstly, health benefits owing to the pre-reform status as head of household in a health-insurance society are unlikely to have been accumulated over time by young consumers (Barros et al. (2008)); secondly, we do not believe that company-worker match in case of young Japanese women is related to potential healthcare demand.

5 Data and variables

The Japanese Panel Survey of Consumers (JPSC) was established in 1993 as the first longitudinal study to accumulate representative micro data on Japanese individuals. The data are collected each year in October via surveys of about 1,500 young women (age 24–51) who answer questions about themselves and members of their households. The major advantage of the Japanese Panel Survey of Consumers for the purposes of analyzing consumer demand for healthcare is its longitudinal character, the existence of questions on the type of health insurance, the amount of healthcare expenditure, health status, and life style.

We restrict the sample of Japanese Panel Survey of Consumers to 2000-2010, as these rounds allow using healthcare expenditure and self-assessed health. The dependent variable "healthcare" is imputed as medical inflation-adjusted healthcare expenditure for outpatient services and drugs covered by health insurance (to account for fee schedule revisions) and is measured as the number of unified fee schedule points. The quality of matching is ensured by using covariates that explain most of variation of the imputed variable in the auxiliary sample (Japan Household Panel Survey); combining matching and regression to avoid imputation bias; examining the distance between matched observations, and analyzing distributions of the imputed variable in the main and auxiliary samples.

The binary variable "coinsurance rate" is constructed to reflect the level of nominal coinsurance for outpatient services and drugs: it equals unity for 30% coinsurance and zero for 20% coinsurance (Ii and Ohkusa (2002a)).[12] Covariates rated to healthcare expenditure are total pre-tax household income (recalculated in 2010 real terms), age, coinsurance rate, and binary variables for poor health, higher education and urban residence.

INSERT Table 3 HERE

The number of respondents of Japanese Panel Survey of Consumers in 2000-2010 varies from 1,376 to 2,284. Since healthcare expenditure is not subdivided with regards to the household member it is paid for, our analysis deals with the sample of unmarried women without children. We exclude women with serious health problems (depression or an illness that required hospitalization) and focus at non-negative healthcare expenditure. This leads to the unbalanced panel of 796 individuals (2203 observations in the pooled data). Finally, difference-in-difference estimations, which require the presence of positive healthcare expenditure both in 2000-2002 and 2003-2010 limit our sample only to 128 individuals.

6 Empirical results

6.1 Models for positive healthcare expenditure

6.1.1 Model comparison

Normality and Wald tests show that the errors in the panel data loglinear finite mixture model are nonnormal but homoskedastic. The result corresponds to the findings about adequate fit of normal mixtures in predicting healthcare costs and makes it possible to obtain unbiased estimates with Duan's (1983) smearing factor. However, experimenting with various finite mixture generalized linear models, we find that models with exponential and Weibull distribution families provide better fit in terms of mean squared error (MSE) than the loglinear model in case of the whole sample. Moreover, the three-compenent model with a Weibull distribution family gives the best fit in terms of mean absolute prediction error (MAPE) (Table 4).

INSERT Table 4 HERE

The Wald test shows that the shape parameter in the Weibull distribution family is significantly different from unity in the second component. Consequently, we consider the generalized linear model with Weibull

[12] Our sample excludes people who had an illness that required hospitalization. Therefore, the analysis does not deal with coinsurance rates for inpatient care.

distribution family as the preferred model among other generalized linear models. In choosing the number of components we note that with 4 classes the algorithms failed to converge. So we use the values of log likelihood function, Akaike information criterion and chi-squared computed according to Andrews (1988) as goodness-of-fit statistics to choose between one-, two- and three-component models. We establish that with exception of goodness-of-fit χ^2 in comparison with the two-component model, the preferred models have three components (Table 5).[13] Note that three-component generalized linear model with a Weibull distribution family may be preferred to corresponding two-component models according to raw bias, MAPE and MSE. The three component loglinear model provides better fit if compared to two-component model only in terms of MAPE and MSE. Nonetheless, the three-component model may not be preferred to teh two-component models according to some criteria, particularly in the holdout sample in crossvalidation analysis. At the same time loglinear model gives the best fit in terms of residuals for the component with higher healthcare expenditure. Therefore, we proceed with estimations both in the two-component and three-component model framework, using loglinear model and generalized linear model with a Weibull distribution family.

INSERT Table 5 HERE

6.1.2 Price effects

The estimations with panel data finite mixture models reveal that the population of young and middle-aged Japanese women decomposes into groups with high and low (or high, medium and low) healthcare expenditure. The models uniformely demonstrate that the mean value of unified fee schedule points in the subpopulation with the highest healthcare expenditure is more than 2 times larger than in the groups with lower healthcare expenditure.[14]

The marginal effect of the coinsurance rate on healthcare expenditure is negative. The effect is larger in absolute terms in the subpopulations with high or medium healthcare expenditure in the two-component (or three-component) loglinear model, but is statistically insignificant. In case of generalized linear model with Weibull distribution family marginal effect is statistically significant in each component of a two-component model, and is larger in absolute terms for subpopulation with high expenditure. As regards three-component model, marginal effect is the strongest among consumers with medium expenditure and

[13] Following Andrews (1988), we use rectangular partitioning and the simple computation of the statistics. To account for annual effects we sum over individual clusters in matrix H, see Appendix A for details.

[14] Indeed, in case of a two component loglinear model $Ey_1 = 2641.27$ (st.deviation 712.06), while $Ey_2 = 1031.66$ (st.dev. 229.50). Generalized linear model with Weibull distribution family with two components produces very similar estimates: $Ey_1^{glm} = 2751.66$ (st.dev. 703.84), $Ey_2^{glm} = 1223.73$ (st.dev. 355.07). The three component loglinear model yields $Ey_1 = 3765.20$ (st.dev. 1851.54), $Ey_2 = 1686.24$ (st.dev. 309.88), $Ey_3 = 519.11$ (st.dev. 253.40). Generalized linear model with a Weibull distribution family gives slightly lower mean values of the dependent variable for the first and second component, and higher mean value for the third component: $Ey_1^{glm} = 2847.45$ (st.dev. 679.29), $Ey_2^{glm} = 1438.01$ (st.dev. 415.63), $Ey_3^{glm} = 611.41$ (st.dev. 284.28).

is statistically insignificant for the low-expenditure subpopulation (Table 6). Large absolute values of the marginal effects in the second component of the two- or three-component model with a Weibull distribution family may be explained by selection bias (see section 6.3.1).

The binary variable for poor health has positive values of marginal effects, which are larger for subpopulations with high expenditure. Age and household income are significant in each component in most of the models. In case of the three-component Weibull GLM, urban residence and higher education are significant.

Finally, we estimate the arc elasticity of a rise in nominal coinsurance rate from 20 to 30 percent in each component of the loglinear model, which has fewer potential problems with sample selection if compared to Weibull GLM. In case of a two-component model the arc elasticity is -0.246 (st.error 0.029)[15] and -0.205 (st. error 0.029) for subpopulations with high and low expenditure, respectively. The three component loglinear model yields arc elasticities of -0.348 (st.error 0.048), -0.133 (st. error 0.023) and -0.199 (st. error 0.066) for subgroups with high, medium and low healthcare expenditure. The absolute value of arc elasticity is larger for components with higher healthcare expenditure. The fact is similar to Bago D'Uva's (2006) finding with RAND data on higher arc elasticity of coinsurance rate in a moderate interval (the rise from 0 to 25 percent) for subpopulation with higher number of doctor visits.

INSERT Table 6 HERE

6.1.3 Posterior analysis of component membership

For the purposes of detailed analysis, the regressions of log $P(i \in j)$ exploit binary variables for each category of self-assessed health. The estimations demonstrate that "very poor health condition" (the lowest category) has a positive impact on the probability of belonging to the class with high healthcare expenditure, while "poor health condition" (the second bottom category) may have a negative significance. Higher household income significantly increases the probability of having higher healthcare expenditure. Higher education is negatively significant in explaining the probability of higher expenditure in the two-component models, and urban residence is positively significant. The facts may be explained by better health status of women with higher education, and larger supply of physicians in urban areas (Table 7). Coinsurance rate proved insignificant and is not included in the list of covariates.

INSERT Table 7 HERE

[15]Estimated using delta method

6.1.4 Crossvalidation

The crossvalidation analysis uses 50 replications with randomly chosen 80% of respondents (i.e. 637 individuals) as a training sample and 20% as a holdout sample (159 individuals). So the unbalanced panel is 1691 to 1825 observations (out of 2203) in the training sample, and 378 to 512 in the holdout sample.

Using the training samples, we conduct estimations with one-, two- and three-component loglinear models and generalized linear models with Weibull distribution family. The values of log likelihood function, Akaike information criteria and Andrews (1988) χ^2 are then computed for corresponding holdout sample. With exception of AIC in the comparison with one-component model, the three-component loglinear model is preferred over models with one or two components in the training sample. As regards generalized linear model with Weibull distribution family, the three-component model is preferred to the one-component model according to all criteria and to the two-component model according to log-likelihood function and AIC. The results for holdout sample are worse than for the training sample, which may be explained by relatively small size of the holdout sample. Yet, the three component model may be preferred to the one- or two-component model according to most criteria in case of generalized linear model with a Weibull distribution family and according to Andrews (1988) χ^2 in case of loglinear model (Tables 8-9).

INSERT Table 8 HERE

INSERT Table 9 HERE

6.2 Treatment effect

The major limitation of our analysis is small sample size, since, owing to attrition bias, data for both pre- and post-reform periods are only available for 128 respondents in the JPSC. Consequently, as our analysis assumes averaging component-specific treatment effects over the size of component, we exploit only finite mixture models with two components: 65 (43) respondents in component 1 and 63 (85) respondents in component 2 in the loglinear model (Weibull GLM), respectively (Table 10). Overall, estimations show that in each component of the model compared to the control group with similar socio-demographic characteristics, the amount of healthcare expenditure of the treatment group decreases after the rise in the coinsurance rate. The finding corresponds to Winkelmann's (2006) results in assessing effect of the introduction of drug copayments on doctor visits in Germany: larger absolute value of the average treatment effect in difference-in-difference estimations for quantiles of frequent users. Contrasting the ATE coefficients with linear and nonlinear CATE estimators reveals that nonlinear price effects are present only in the component with high expenditure.

INSERT Table 10 HERE

6.3 Internal validity

The use of representative data for adult population of Japanese consumers (Japan Household Panel Survey, 2008-2010) allows investigating internal validity of our analysis in terms of goodness of fit of loglinear and generalized linear models, potential bias in estimated coefficients of covariates of healthcare expenditure and posterior probability of component membership. Namely, we introduce binary variables for females, marital status and presence of children. In case of posterior analysis of component membership we add lifestyle and health risk variables, accounting for checkups, attending gym, presence of obesity or overweight, and the values of index of psychological distress (Ben-Sira (1982)), which are present in the survey. Unfortunately, we can explicitly employ in the price variable, as nominal coinsurance rate has a flat value of 30% for all nonelderly respondents in JHPS. Moreover, data on urban residence is absent in JHPS. Therefore, to assess internal validity of our estimates we exploit the post-2003 sample of JPSC, so that nominal coinsurance rate was equal for all consumers and could be disregarded as a regressor. Additionally, we exclude urban residence from teh list of covariates in JPSC. Descriptive statistics for nonelderly sample of JHPS, subsample of JHPS consumers in the same age cohort as respondents of JPSC, and the sample of JPSC in 2003-2010 are presented in Appendix B.

6.3.1 Model selection and marginal effects

We find that generalized linear model with a Weibull distribution family provides the best fit among other GLMs and gives superior fit in terms of MAPE compared to loglinear model in case of the sample of all nonelderly consumers of JHPS or only consumers of age 24-51. To assess potential selection bias owing to sampling procedure in JPSC we use the subsamples of JPSC and JHPS for young consumers (24-51). The results of the estimations indicate that age, household income, binary variables for poor health and higher education generally have similar significance and similar values of marginal effects for both samples in each corresponding model. Moreover, the shape parameter for Weibull distribution is close to unity in the component with higher expenditure in both samples (Table 11).

INSERT Table 11 HERE

To evaluate potential bias due to selecting unmarried women without children in JPSC (age 24-51), we use subsamples of all nonelderly adult consumers (age 20-69) and young consumers (age 24-51) of JHPS. We focus on marginal effects of the binary variables, accounting for females, unmarried and absence of children, which are added to the list of covariates. The three binary variables prove insignificant in case of loglinear models both for all nonelderly consumers and young consumers. As regards generalized linear model with a Weibull distribution family, absence of children has positive marginal effects in all components, and the values are larger in the component with the highest healthcare expenditure. Marital status is significant only in explaining healthcare expenditure of all consumers in components 2 and 3 of a three-component model. Female dummy has a positive marginal effect in the groups with the highest healthcare expenditure.

Arguably, presence of children leaves fewer job market possibilities for young Japanese women, leading to their enrollment in National Health Insurance or as a dependent in other schemes, where nominal coinsurance rate is higher. So *absence* of children is negatively related to the size of nominal coinsurance rate and given "nochild" dummy has a positive effect on healthcare expenditure, the bias of the price effect owing to exclusion of this variable is downward in all components of the model. Female dummy may be viewed as positively related to the size of nominal coinsurance rate in Japan, so it leads to upward bias in the price effect in the component with the highest expenditure. The facts may indicate the overestimation of the absolute value of the price effect in the second component of the model with a Weibull distribution family, owing to the potential downward bias.

As regards contrasting all adult consumers and consumers of age 24-51, we may note that the effect of income is larger for all consumers in the component with higher healthcare expenditure and the effect of age is larger in the component with lower expenditure. Binary variable for poor health is significant primarily for young consumers.

The values of mixing proportions (prior probabilities of component membership) in the loglinear and generalized linear model, as well as the values of the shape parameter for Weibull distribution are similar for both subsamples (Table 12).

INSERT Table 12 HERE

6.3.2 Component membership

The probability of belonging to the component with the highest healthcare expenditure is negatively related to female dummy, unmarried status (Weibull GLM with 3 components) and absence of children (in case of young consumers).[16] If the effect of the three selection variables is linearly separable, we may sum up their coefficients and argue that exploiting the subsample of unmarried women without children may have led to underestimation of the size of the component with the highest healthcare expenditure.

As regards lifestyle and health risk variables, the probability of being attributed to the component with the highest healthcare expenditure is positively related to having poor health, being overweight or obese, undergoing additional checkups, smoking or drinking heavily (the latter only for young consumers). Education is negatively related to the first component membership. Attending gym or buying health supplements

[16] Absence of children is positively related to the probability of belonging to the first component for all adult consumers.

has no effect on component membership. It should be noted that higher values of the psychological distress index (i.e. lower degree of stress) is positively associated with the membership in the component with the highest healthcare expenditure. The fact may reflect high degree of trust between physicians and patients in Japan.

INSERT Table 13 HERE

7 Discussion

Copayments and coinsurance have been widely used in the U.S. since the 1970s and are currently given special emphasis within Medicare's part D reform (Claxton et al. (2013)). Other recent examples include: introduction of coinsurance rate for retirees in Spain in 2012; user fees for healthcare services in the Czech Republic since 2008; a fixed copayment for unwarranted access to emergency hospital departments in Italy since 2007; drug cost-sharing for Taiwanese elderly since 1999; an increase in copayments for prescriptions within the 1997 German health reform; establishment of copayments for primary care for a group of consumers in Austria in 1997; the coinsurance rate within the 1996 compulsory health insurance reform in Switzerland; a rise of the coinsurance rate for selected physician services in Belgium in 1994; introduction of a coinsurance rate for physician visits for a group of French consumers in 1994; and per visit co-payment in South Korea since 1986 (Puig-Junoy et al. (2013); Bryndova et al. (2009); Scalzo et al. (2009); Liu and Romeis (2004); Winkelmann (2004); Reichmann and Sommersguter-Reichmann (2004); Cockx and Brasseur (2003); European Observatory on Healthcare Systems (2000); Chiappori et al. (1998); Jung (1998)).

Our estimations assessing the effect of a rise in nominal coinsurance rates on healthcare expenditure of young and middle-aged women in Japan reveal statistically stronger negative effect in the group with higher healthcare expenditure. The finding corresponds to the empirical literature, which commonly demonstrates more noticeable negative effect of healthcare price variables (insurance coverage, copayments) in the component of high users of healthcare (Schmitz (2012); Farbmacher et al. (2011); Bago D'Uva (2006); Winkelmann (2006); Deb and Trivedi (2002)). The novel result of our estimates is the presence of nonlinearity in the effect in the subpopulation with high expenditure.

The findings have several policy implications. As regards planning and welfare issues, heterogeneity in consumer response to coinsurance rate is integral in predicting the effect on healthcare spending for subpopulations. Our estimations demonstrate that marginal effects of price on healthcare expenditure differ 2-3 times across subpopulations, and subpopulations with the highest healthcare expenditure suffer most owing to the natural experiment of the rise in nominal coinsurance rate. The market perspective may be concerned with designing plans with different coinsurance rate for subpopulations with different elasticity.

Moreover, we discover that the effect of coinsurance may vary conditional on other covariates (i.e. income, state of health) and the impact may be nonlinear. Finally, the observable correlates of subpopulation membership may be exploited for disentangling the groups with high and low demand for healthcare, and subsidizing seriously sick consumers, who have high healthcare expenditure and low price response.

We should note limitations of our analysis. Since the data on healthcare expenditure which can be retrieved from the Japanese Panel Survey of Consumers deals with out-of-pocket expenditure paid personally by the respondent, our analysis was limited to women. However, women generally take better care of their health than men, so healthcare use (Jiménez-Martín et al. (2004)), and hence healthcare expenditure by women may be higher than that of the general population of the corresponding age. Moreover, in the case of the analysis with the data for men and women, the binary variable with unity value for women is positive in explaining healthcare use in the component of high users (Sarma and Simpson (2006)). Consequently, the relative size of the coefficients for price effect in the components of the model may differ for men and women. As regards the significance of age and household income, the finite mixture models estimated separately for men and women reveal that these covariates generally have similar values in the corresponding components of the models for healthcare demand (Bago D'Uva (2005); Jiménez-Martín et al. (2004)). Another 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 healthcare prices (Yoshida and Takagi (2002)). The final limitation is small sample size of our subpopulations, particularly in the posterior difference-in-difference analysis with the group having high demand for healthcare. Consequently, the findings of the CATE estimations should be taken as tentative.

8 Conclusion

The paper combines finite mixture models and matching estimators to study the effect of the nominal coinsurance rate on outpatient healthcare expenditure of Japanese women aged 24-51. We find that the effect on the amount of healthcare expenditure is heterogeneous and nonlinear, and is stronger in subpopulation with high healthcare expenditure.

Methodologically we discover adequate fit between the panel data finite mixture loglinear model and the panel data generalized linear model with Weibull distribution family. The models demonstrate that adult Japanese consumers separate into components with high, medium and low healthcare expenditure, and component membership is explained by health risk and lifestyle variables.

Appendix A Andrews (1988) chi-square test

Andrews (1988) considers the conditional distribution f Y_i given $\mathbf{X}_i$, which is the parametric family $\{f(y|x,\theta)\}$. $\mathbf{D}$ is a class of partitions of $\mathbf{Y}\times\mathbf{X}$, where each partition contains J sets (i.e. groups of cells) from a class $\mathbf{C}$ of measurable sets in $\mathbf{Y}\times\mathbf{X}$.

A random element of $\mathbf{D}$ is denoted $\hat{\Gamma}$ and converges in probability to a fixed partition $\Gamma\in\mathbf{D}$ if the cells continuously depend on $\hat{\boldsymbol{\theta}}$ and $\hat{\boldsymbol{\theta}}$ converges in probability to a non-random vector. Denote $\nu_n(\Gamma,\boldsymbol{\theta}_0)$ a normalized measure of the difference between the observed numbers of observations in $\Gamma_1,...,\Gamma_J$ and the expected numbers according to $f(\mathbf{y}|\mathbf{x},\boldsymbol{\theta}_0)$ and the observed covariates $\mathbf{X}$ (here n is sample size). The chi-square test statistics (eq.5) is

$$\chi^2_n(\hat{\Gamma},\hat{\boldsymbol{\theta}})=\nu_n(\hat{\Gamma},\hat{\boldsymbol{\theta}})'\hat{W}\nu_n(\hat{\Gamma},\hat{\boldsymbol{\theta}})', \tag{14}$$

where W is some generalized inverse of covariance matrix for vectors of indicator functions $\gamma(Y_i,X_i)$, $i=1,...,n$. The degrees of freedom in the statistics are the maximum number of groups of cells in Γ, so that each covariate belongs to cells in one and only one group.

A simple form of chi-square statistics (appendix A.5 in Andrews (1988)) is

$$\chi^2_n(\hat{\Gamma},\hat{\boldsymbol{\theta}})=\mathbf{1}'H(H'H)^+H'\mathbf{1} \tag{15}$$

Here $H=[AB]$, A is $n\times J$ matrix with i-th row $\hat{\Gamma}(Y_i,X_i)'-F(\hat{\Gamma},X_i,\hat{\boldsymbol{\theta}})$, where $\hat{\Gamma}(Y_i,X_i)$ is a vector with unity value the j-th partition, which contains observation (Y_i,X_i) and zeros for other coordinates, and F is the cumulative distribution function (in our case multivariate normal for $\log y$ of Weibull for $exp(-\mathbf{x}'\boldsymbol{\beta})$.

B is $n\times\dim\boldsymbol{\theta}$ matrix with i-th row $\partial/\partial\theta\log f(Y_i|X_i,\hat{\theta})'$, where $\boldsymbol{\theta}$ is the vector of all parameters in the corresponding model, and $\mathbf{1}$ is a vector of ones.

Our implementation of Andrews (1988) chi-square test uses rectangles, when the border hyperplanes are defined as $\log y\ =\mathrm{med}(\log y)$ for loglinear model or $y=\mathrm{med}\,y$ for Weibull generalized linear model, $x_k=\mathrm{med}\,x_k$ for $k=1,...,K$ continuous covariates and $x_s=\mathrm{mean}\,x_s$ for $s=1,...,S$ binary covariates. We exploit 4 covariates, which explain most of variation in the dependent variable: log income, age, poor health and coinsurance rate, so the number of partitions of $\mathbf{Y}\times\mathbf{X}$ is $2^5=32$. By construction the degrees of freedom for the test equal 16. Our partitioning allows using simle form of the statistics, and we account for cluster effects (i.e. panel data structure of data) summing the elements of H over clusters.

The analysis of crossvalidation assumes that the log likelihood function is fully maximized in the training sample, so all the elements of B (the derivatives of log L) are zero. Consequently, we follow Deb and Trivedi (2002) to set $H=A$ and compare the values of χ^2 statistics for finite mixture models with different number of components, since the null hypothesis is likely to be rejected for each model, owing to overparametrization.

Appendix B Surveys

B.1 Japan Panel Survey of Consumers

The Japanese Panel Survey of Consumers (JPSC) was established in 1993 as the first longitudinal study to accumulate representative micro data on Japanese individuals. The surveys are conducted as person-to-person interview by The Institute for Research on Household Economics from October 1 to October 31 each year. Young women (age 24–51 as of 2010) answer questions about themselves and members of their households. The major advantage of the Japanese Panel Survey of Consumers for the purposes of analyzing consumer demand for healthcare is its longitudinal character, the existence of individual-level questions on the type of health insurance, and self-assessed health and family-level question on the amount of healthcare expenditure (in September of the survey year). 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 of females from the population of each subgroup of cities, towns, and villages (a, b, and c) in each geographical zone with regard to the following two characteristics: age and marital status. The constructed cohort A consisted of 1,500 women of age 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 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 a household /unmarried and living alone women were 3 to 4 to 7 in cohorts C and D. Cohort C are women of age 24-29 as of March 2003, and cohort D are women of age 24-28 as of March 2008.

B.2 Japan Household Panel Survey

The Japan Household Panel Survey was established in 2009 by Keio University Joint Research Center for Panel Studies as a nationally representative annual survey of adults (with regard to sex and each age group: 20s, 30s, 50s, 60s and over). The surveys are conducted on January 31. Respondents above 20 year-old answer a wide range of individual-level questions, including the amount of inpatient and outpatient healthcare expenditure, covered and not covered by health insurance, in the preceding year.

Respondents were selected in 2009 according to a two-stage random sampling procedure. At the first stage, all localities in Japan were divided into 24 strata: 3 groups of localities (designated cities, other cities, towns and villages) were selected in each of the 8 geographic zones. The sample size for each group was determined according to the share of its population in the National Residents Register (as of March 31, 2008). The survey areas in each group were then randomly selected out of enumeration districts for the 2005 National Census, so that approximately 10 people would be selected to be surveyed in each area. The preliminary sample at the second stage was 9,633 people. The response rate was 41,5% and the number of respondents was 4,022. With respect to the way of filling in the questionnaire, localities were randomly divided into 2 types: 1) self-response (questionnaires were distributed to respondents, who filled them in and then submitted to the interviewers at their second visit - drop-off pick-up method); 2)self-response supplemented by person-to-person interview (questionnaires were distributed to respondents, who filled them in and then submitted to the interviewers at their second visit; the interviewers also asked respondents questions at the second visit - drop-off pick-up method plus an interview). Additionally, all respondents were offered a web-based answering option.

Sample sizes in 2010 (round 2) and 2011 (round 3) are respectively 3,470 (86.3% response rate of individuals surveyed in round 1) and 3,154 (90,9% response rate individuals surveyed in round 2 and 6 individuals, surveyed in round 1, who wished to participate).

B.3 Descriptive statistics for JPSC and JHPS samples in analysis of internal validity

We use the representative sample of nonelderly Japanese consumers from Japan Household Panel Survey (2008-2010), i.e. consumers of age 19-69 (In Japan 20-year-olds are considered adults, yet three respondents in the sample have full age 19). Additionally, the analysis exploits a subsample of young JHPS consumers, who belong to the same age cohort as respondents of JPSC: 24-51. We exploit the post-2003 sample of JPSC, so that nominal coinsurance rate was equal for all consumers.

Healthcare expenditure for JPSC corresponds to September of the survey year. In case of JHPS healthcare expenditure is reported on the annual basis, so we compute average monthly expenditure.

The values of descriptive statistics show that the subsamples of JPSC and young JHPS consumers are close in terms of household income, prevalence of poor health and higher education. Healthcare expenditure of JPSC consumers is higher, which may reflect recall bias of JHPS respondents. However, we assume equal recall bias for healthcare expenditure covered and not covered by health insurance. This allows using the share of healthcare expenditure outside health insurance in JHPS for imputations with JPSC.

INSERT Table 14 HERE

Appendix C Imputations

C.1 Nominal coinsurance rate

Enrollment in a health insurance plan as head of household or as dependent is specified in the Japan Panel Survey of Consumers questionnaire since 2004 (round 12). we assume that a respondent was insured as head of household in company-managed health insurance or in benefit schemes of mutual-aid associations in 2000-2003 (rounds 8-11) if she worked in the corresponding year. We test this assumption by using the actual data for rounds 12-18 and find that it holds in 99.2% of cases for company-managed health insurance and in 98.9% of cases for mutual-aid benefit schemes. Additionally, the type of health insurance is not reported by 3-13% of respondents in various years. We fill in the missing values using the available data for the previous or subsequent year. As was noted in Section 3, owing to the system of medical benefits and medical expenditure deductions, the consumer price of healthcare may be lower than the nominal coinsurance rate, but various benefits and exemptions mostly apply to inpatient care, which is not studied in our analysis.

C.2 Self-assessed health

Respondents of Japan Panel Survey of Consumers are only asked to provide subjective assessment of their state of health since 2002 (round 10). The value of round 10 can be used to fill in the missing values for state of health in preceding rounds. Using the data for rounds 10-18 we find that the actual value and the forwarded value of the binary variable for poor state of health (with unity value corresponding to self-assessed health evaluated as “not very healthy” or “not at all healthy”) in case of one-, two- or three-year lags differed for 7.2%, 9.8%, and 10.9% of respondents, respectively. Choosing the 10% level, we fill in the missing data for subjective assessment of state of health for the two rounds 8 and 9 and limit our sample to 2000-2010 (rounds 8-18). In order to check robustness, we carry out estimations for 2002-2010 only (rounds, in which the "true" values of state of health are available). The results of the estimations with the data for 2000-2010 and 2002-2010 are similar in terms of the number of components, good fit of the model, and values of coefficients in each component.

C.3 Healthcare expenditure

Healthcare expenditure is reported in the Japan Panel Survey of Consumers since 1998 (round 6) and encompasses all expenditure on medical services, drugs, and health goods.[17] In this formulation healthcare expenditure may incorporate the cost of health goods not covered by health insurance. Consequently, we use the data of Japan Household Panel Survey to impute the share of expenditure on health goods not covered by health insurance in total consumer healthcare expenditure. Formally, denote analyzed subsample of females in JPSC as $S_1 = \{\mathbf{x}_i\}, i = 1, ..., N$. We select a subgroup $S_2 = \{q_j, \mathbf{z}_j\}$ of female respondents in JHPS, who have no inpatient healthcare expenditure and belong to the same age cohort as respondents in our JPSC sample. Here q_j is the share of healthcare expenditure not covered by health insurance in total healthcare expenditure, $\mathbf{z}$ are covariates, explaining q_j in sample S_2 and $\mathbf{x}$ are counterparts if $\mathbf{z}$ in sample S_1.

For each round of JPSC we find matches for S_1 in S_2, based on age and the binary variable for poor state of health (exact matching[18] on the latter variable), since these two variables are the only significant covariates in explaining y_j in JHPS. We exploit regressions with two parameter beta distribution or generalized linear models with log link and binominal distribution family and get similar results about the significance of coefficients for covariates. To increase sample size for imputations we use pooled data of JHPS, as coefficients for age and poor health in annual regressions explaining proportion q_j differ neglibly. To account for potential tradeoff between healthcare services and drugs, covered and not covered by health insurance, we use two types of consumer price indexes: 1) for insurance-covered medical goods, services and drugs; 2) for medical goods, not covered by health insurance. Both indexes proved insignificant and are not employed in the imputation.

We use Stata's module *nnmatch* (Abadie et al. (2004)), which employs Mahalanobis metric with the inverse of the sample variance/covariance matrix, so distance between matched pairs of observations is calculated as $d_m(x_i, z_j) = (x - z)'\Sigma_{\mathbf{x}}^{-1}(x - z)$. The advantage of Mahalanobis metric is the ability to handle

[17]Arguably, health insurance premiums are not regarded as a potential component of healthcare expenditure. Indeed, the prevalence of zero reported healthcare expenditure among heads of household, who pay premiums and hence cannot have zero healthcare expenditure if premiums are considered a part of expenditure, is 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.

[18]The weight on the variable is 1000 larger than weights on other variables.

potentially correlated covariates, measured on different scales. Additionally, the imputation bias is corrected through matching and regression (Abadie and Imbens (2011)). Since $\mathbf{x}$ and $\mathbf{z}$ have the same meaning and same units in both samples, we do not have to normalize them, as normalization might increase the bias. Moreover, age is calculated in full years in JPSC, which leads to more than one match in JHPS. The matching and regressions results in 100% of exact matches, and mean distance between matched pairs in various years is less than 0.001 (min 0, max 0.23, standard deviation less than 0.007). Finally, for each observation i in JPSC the imputed share is calculated as the mean value over all q_j for the minimum number of matches in JHPS.

As a result, the product of total healthcare expenditure in the JPSC and unity less the imputed share produces healthcare expenditure covered by health insurance. The mean values of the imputed q are 0.3874 to 0.4243 in various years, which is extremely close to the mean value of q in JHPS is 0.3884.

To check robustness of the estimates, given the imputed empirical distribution has fewer exact zero or unity values than the distribution of q in JHPS, we conduct the following censoring procedure. We compute the values for percentiles of observations, which have the share below 0.1 (above 0.9) in JHPS (percentiles 29.92 and 83.12, respectively), and assign zero (unity) value to the corresponding percentiles of the imputed empirical distribution in JPSC. After such censoring the difference in the mean values of the imputed share and the share in JHPS is negligible and the results with respect to the significance and the values of the effects in each component of the model are similar for non-censored and censored subsamples.

The imputation procedure might cause a possible bias, as the JPSC asks for healthcare expenditure in September of the corresponding year, while the JHPS collects information about annual healthcare expenditure. We rely on assumptions about absence of seasonality in healthcare expenditure by adult Japanese consumers in September[19] and on equal recall bias (within a 12-month period) for healthcare expenditure which is covered and not covered by health insurance. Finally, although the imputations enable computation of the trade-off between healthcare expenditure that is covered and not covered by health insurance, our analysis does not allow identification of the potential dependence of the share of insurance-covered healthcare expenditure on the coinsurance rate. To the best of our knowledge there is no consumer survey or statistical data, which differentiates between healthcare expenditure in Japan that is covered by health insurance and not covered.

[19]The season for respiratory diseases is late autumn-early winter.

References

Abadie, A., D. Drukker, J. L. Herr, and G. W. Imbens (2004). Implementing matching estimators for average treatment effects in Stata. *Stata Journal 4*, 290–311.

Abadie, A., J. L. Herr, G. W. Imbens, and D. M. Drukker (2004). NNMATCH: Stata module to compute nearest-neighbor bias-corrected estimators. *Statistical Software Components*.

Abadie, A. and G. Imbens (2002). Simple and bias-corrected matching estimators for average treatment effects.

Abadie, A. and G. W. Imbens (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics 29*(1).

Aday, L. and R. Andersen (1974). A framework for the study of access to medical care. *Health Services Research 9*(3), 208–220.

Agresti, A. (2007). *An Introduction to Categorical Data Analysis.* Wiley-Interscience.

Andersen, R. (1995). Revisiting the behavioral model and access to medical care; does it matter? *Health and Social Behavior 36*(1), 1–10.

Andrews, D. W. (1988). Chi-square diagnostic tests for econometric models: Introduction and applications. *Journal of Econometrics 37*, 135–156.

Angrist, J. and J. Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton University Press.

Arai, Y. and N. Ikegami (1998). An overview of the Japanese healthcare system. *Journal of Public Health Management 20*(1), 29–33.

Arrow, K. (1963). Uncertainty and the welfare economics of medical care. *American Economic Review 53*, 941–973.

Atella, V., F. Brindisi, P. Deb, and F. Rosati (2004). Determinants of access to physician services in Italy: A latent class seemingly unrelated probit approach. *Health Economics 13*, 657–668.

Babazono, A., M. Miyazaki, T. Imatoh, H. Une, E. Yamamoto, T. Tsuda, K. Tanaka, and S. Tanihara (2005). Effects of the increase in co-payments from 20 to 30 percent on the compliance rate of patients with hypertension or diabetes mellitus in the Employed Health Insurance System. *International Journal of Technology Assessment in Healthcare 21*(2), 228–233.

Babazono, A., T. Tsuda, E. Yamamoto, Y. Mino, H. Une, and A. Hillman (2003). Effects of an increase in patient copayments on medical service demands of the insured in Japan. *International Journal of Technology Assessment in Healthcare 19*(3), 465–475.

Bago D'Uva, T. (2005). Latent class models for use of primary care: evidence from a British panel. *Health Economics 14*, 873–892.

Bago D'Uva, T. (2006). Latent class models for utilization of healthcare. *Health Economics 15*(4), 329–343.

Bago D'Uva, T. and A. Jones (2009). Healthcare utilization in Europe: New evidence from the ECHP. *Journal of Health Economics 28*, 265–279.

Baldi, I., E. Pagano, P. Berchialla, A. Desideri, A. Ferrando, F. Merletti, and D. Gregori (2013). Modeling healthcare costs in simultaneous presence of asymmetry, heteroscedasticity and correlation. *Journal of Applied Statistics 40*(2), 298–310.

Barros, P., M. Machado, and A. Sanz-de Galdeano (2008). Moral hazard and the demand for health services: A matching estimator approach. *Journal of Health Economics 27*(4), 1006–1025.

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

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

Bertrand, M., E. Duflo, and S. Maullainathan (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics 119*(1), 249–275.

Bessho, S. and Y. Ohkusa (2006). When do people visit a doctor? *Healthcare Management Science 9*(1), 5–18.

Bhattacharya, J., W. Vogt, A. Yoshikawa, and T. Nakahara (1995). The utilization of outpatient medical services in Japan. *The Journal of Human Resources 31*(2), 450–476.

Biro, A. (2013). Copayments, gatekeeping, and the utilization of outpatient public and private care at age 50 and above in Europe. *Health Policy 111*, 24–33.

Bryndova, L., K. Pavlokova, T. Roubal, M. Rokosova, M. Gaskin, and E. van Ginneken (2009). Czech republic: Health system review. *Health Systems in Transition 11*(1), 1–122.

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

Busse, R. and A. Riesberg (2004). Health care systems in transition: Germany. Technical report, WHO Regional Office for Europe on behalf of the European Observatory on Health Systems and Policies, Copenhagen.

Cameron, A. C. and P. K. Trivedi (2013). *Regression Analysis of Count Data.* Number 53. Cambridge University pPess.

Campbell, J. and N. Ikegami (1998). *The Art of Balance in health policy: Maintaining Japan's Low Cost, Egalitarian System.* Cambridge University Press.

Chalkley, M. and J. Malcomson (2000). Government purchasing of health services. In *Handbook of Health Economics*, pp. 847–890. Elsevier.

Chiappori, P., F. Durand, and P. Geoffard (1998). Moral hazard and the demand for physician services: First lessons from a French natural experiment. *European Economic Review 42*, 499–511.

Claxton, G., M. Rae, N. Panchal, A. Damico, H. Whitmore, N. Bostick, and K. Kenward (2013). Health benefits in 2013: Moderate premium increases in employer-sponsored plans. *Health Affairs 32*(9), 1–10.

Clogg, C. (1981). New developments in latent structure analysis. In D. M. Jackson and E. F. Borgatta (Eds.), *Factor Analysis and Measurement*, Beverly Hills, California, pp. 215–246. Sage.

Cockx, B. and C. Brasseur (2003). The demand for physician services. evidence from a natural experiment. *Journal of Health Economics 22*, 881–913.

Collins, L. and S. Lanza (2010). *Latent Class and Latent Transition Analysis with Applications in the Social, Behavioral, and Health Sciences.* Hoboken, New Jersey: John Wiley & Sons.

Crew, M. (1969). Coinsurance and the welfare economics of medical care. *American Economic Review 59*(5), 906–908.

Crump, R. K., V. J. Hotz, G. W. Imbens, and O. A. Mitnik (2009). Dealing with limited overlap in estimation of average treatment effects. *Biometrika 96*(1), 187–199.

Cutler, D. (2002). Healthcare and the public sector. In A. Auerbach and M. Feldstein (Eds.), *Handbook of Public Economics, Vol.4*, pp. 2186–2189. Elsevier Science.

Dafny, L. and D. Dranove (2006). Regulatory exploitation and the market for corporate control. NBER Working Paper 12438.

Dardanoni, V., D. P. (2009). The effect of supplemental insurance on healthcare demand with multiple information: A latent class analysis. HEDG Working Paper 09/03, The University of York.

Dayton, C. (1999). Latent class scaling analysis. In *Quantitative Applications in the Social Sciences*. Sage Publications.

De Bekker-Grob, E., M. Ryan, and K. Gerard (2012). Discrete choice experiments in health economics: a review of the literature. *Health Economics 21*, 145–172.

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

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

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

Deb, P. and P. Trivedi (2002). The structure of demand for healthcare: latent class verses two-part models. *Journal of Health Economics 21*, 601–625.

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

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

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

Duarte, F. (2012). Price elasticity of expenditure across healthcare services. *Journal of Health Economics 31*, 824–841.

European Observatory on Healthcare Systems (2000). Switzerland. Technical Report AMS 5012667 (SWI), target 19, 2000 R, WHO Regional Office for Europe on behalf of the European Observatory on Health Systems and Policies.

Farbmacher, H., P. Ihle, I. Schubert, J. Winter, and A. Wuppermann (2011). Heterogeneous effects of nonlinear price schedule for ambulatory care. Technical report.

Frees, E., J. Gao, and M. Rosenberg (2011). Predicting the frequency and amount of healthcare expenditures. *North American Actuarial Journal 15*(3), 1–31.

Fujii, M. and M. Reich (1988). Rising medical costs and the reform of japan's health insurance system. *Health Policy 9*, 9–24.

Gerdtham, U. and P. Trivedi (2001). Equity in Swedish healthcare reconsidered: New results based on finite mixture model. *Health Economics 10*(6), 565–572.

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

Greene, W. (2007). *LIMDEP version 9.0. Econometric Modelling Guide.* Econometric Software.

Greene, W. (2012). *Econometric Analysis, 7th ed.* Pearson Education.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy 80*(2), 223–255.

Hamilton, J. (1994). *Time Series Analysis*, Volume 2. Princeton university press.

Hashimoto, M. (1990). *The Japanese labor market in a comparative perspective with the United States: A transaction-Cost Interpretation.* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Heckman, J. and B. Singer (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica 52*(2), 271–320.

Heckman, J. J. and E. J. Vytlacil (2007). Econometric evaluation of social programs, part i: Causal models, structural models and econometric policy evaluation. *Handbook of Econometrics 6*, 4779–4874.

Higuchi, T. (1974). Medical care through social insurance in the japanese rural sector. *International Labor Review 109*(3), 251–274.

Hirano, K., G. Imbens, and G. Ridder (2000). Efficient estimation of average treatment effect using the estimated propensity score. Technical Working Paper 251, NBER.

Hole, A. (2008). Modelling heterogeneity in patients' preferences for the attributes of a general practitioner appointment. *Journal of Health Economics 27*, 1078–1094.

Hornbrook, M., A. Hurtado, and R. Johnson (1985). Healthcare episodes: definition, measurement and use. *Medical Care Research and Review 42*(2), 163–218.

Hsiao, W. C., H. Sapolsky, D. Dunn, and S. Weiner (1986). Lessons of the New Jersey DRG payment system. *Health Affairs 5*(2), 32–45.

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

Ii, M. and Y. Ohkusa (2002b). Should the co-insurance rate be increased in the case of the common cold? An analysis based on the original survey. *Journal of the Japanese and International Economies 16*, 353–371.

Ikegami, N. (1991). Japanese healthcare: low cost through regulated fees. *Health Affairs 10*, 87–109.

Ikegami, N. (1996a). Comparison of pharmaceutical expenditure between Japan and the United States. In N. Ikegami and J. Campbell (Eds.), *Containing Healthcare Costs in Japan*, pp. 121–131. The University of Michigan Press.

Ikegami, N. (1996b). Overview: Healthcare in Japan. In N. Ikegami and J. Campbell (Eds.), *Containing Healthcare Costs in Japan*, pp. 8–18. The University of Michigan Press.

Ikegami, N. (2005). Medical care in Japan. *New England Journal of Medicine 133*(19), 1295–1299.

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

Ikegami, N. (2008). Japan, health system of. In K. Heggenhougen and S. Quah (Eds.), *International Encyclopedia of Public Health, Vol.4.*, San Diego, pp. 1–8. Academic Press.

Ikegami, N. and J. Campbell (1995). Medical care in Japan. *New England Journal of Medicine 133*(19), 1295–1299.

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

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

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

Imai, Y. (2002). Health care reform in Japan. Technical report, OECD Publishing.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics 86*(1), 4–29.

Imbens, G. W. and J. Wooldridge (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature 47*(1), 5–86.

Ishikawa, K., M. Yamamoto, D. Kishi, and T. Nabeshima (2005). New prospective payment system in Japan. *American Journal of Health System Pharmacy 62*, 1617–1619.

Japan Statistical Yearbook (2013). Tokyo: Ministry of Internal Affairs and Communications, Statistics Bureau.

Jiménez-Martín, S., J. M. Labeaga, and M. Martínez-Granado (2002). Latent class versus two-part models in the demand for physician services across the European Union. *Health Economics 11*(4), 301–321.

Jiménez-Martín, S., J. M. Labeaga, and M. Martínez-Granado (2004). An empirical analysis of the demand for physician services across the European Union. *Journal of Health Economics 5*, 150–165.

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

Jung, K.-T. (1998). Influence of the introduction of a per-visit copayment on health care use and expenditures: the Korean experience. *Journal of Risk and Insurance 65*(1), 33–56.

Kan, M. and W. Suzuki (2006). The demand for medical care in Japan: initial findings from a Japanese natural experiment. *Applied Economics Letters 13*(5), 273–277.

Kan, M. and W. Suzuki (2010). Effects of cost sharing on the demand for physician services in Japan: Evidence from a natural experiment. *Japan and the World Economy 22*, 1–12.

Keeler, E. B. and J. E. Rolph (1988). The demand for episodes of treatment in the health insurance experiment. *Journal of Health Economics 7*(4), 337–367.

Kondo, A. and K. Kawabuchi (2012). Evaluation of the introduction of a diagnosis procedure combination system for patient outcome and hospitalisation charges for patients with hip fracture or lung cancer in Japan. *Health Policy 107*, 184–193.

Kondo, A. and H. Shigeoka (2013). Effects of universal health insurance on healthcare utilization, and supply-side responses: evidence from Japan. *Journal of Public Economics 99*, 1–23.

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

Kuwabara, K., S. Matsuda, K. Fushimi, K. Ishikawa, H. Horiguchi, K. Hayashida, and K. Fujimori (2011). Contribution of case-mix classification to profiling hospital characteristics and productivity. *International Journal of Health Planning and Management 26*, e138–e150.

Levitt, S. D. and J. A. List (2007). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic Perspectives 21*(2), 153–174.

Liu, S.-Z. and J. C. Romeis (2004). Changes in drug utilization following the outpatient prescription drug cost-sharing program-evidence from Taiwan's elderly. *Health Policy 68*(3), 277–287.

Lourenco, O. D. and P. L. Ferreira (2005). Utilization of public health centres in Portugal: effect of time costs and other determinants. Finite mixture models applied to truncated samples. *Health Economics 14*(9), 939–953.

Maeda, N. (1978). Study on the medical cost rising by the new policy for the expansion of benefit in health insurance. *Quarterly Social Security Research 14*(2), 33–47. (in Japanese).

Manning, W. G. and J. Mullahy (2001). Estimating log models: to transform or not to transform? *Journal of Health Economics 20*(4), 461–494.

McCutcheon, A. *Latent Class Analysis*.

Mihaylova, B., A. Briggs, A. O'Hagan, and S. G. Thompson (2011). Review of statistical methods for analysing healthcare resources and costs. *Health Economics 20*(8), 897–916.

Ministry of Finance (2012). Heisei 24 nendo ippan kaikei saishutsu yosan (Plan for annual expenditure from the general accounts 2012, March 29, 2012). Technical report.

Ministry of Health, Labor and Welfare (2011). Heisei 23 nenpan kouseiroudouhakusho shiryouhen. [White paper on health, labor, and welfare for 2011, supplementary material].

Ministry of Health, Labor and Welfare (2012a). Heisei 24 nenpan kouseiroudouhakusho shiryouhen. [White paper on health, labor, and welfare for 2012, supplementary material].

Ministry of Health, Labor and Welfare (2012b). Shinryouhouushuuseido-nitsuite [On the system with fee schedule].

Ministry of Health, Labor and Welfare (2013a). Heisei 25 nenpan kouseiroudouhakusho shiryouhen. [White paper on health, labor, and welfare for 2013, supplementary material].

Ministry of Health, Labor and Welfare (2013b). Heisei 26nendo sinryouhoushuu kaiteino sukejuuru (Schedule for the 2014 revision of the fee schedule).

Ministry of Health, Labor and Welfare (2014a). DPC/PDPS shoubyouna koodingu tekisuto (Handbook for coding illnesses in DPC/PDPS, Mar 26).

Ministry of Health, Labor and Welfare (2014b). Heisei 26nendo sinryouhoushuu kaitei-niokeru DPC seido (DPC/PDPS)-no taiyou-nitsuite (gaiyou) (An outline of DPC/PDPS system within the 2014 revision of fee schedule, Mar 26).

Miraldo, M., M. Goddard, and P. Smith (2006). The incentive effects of payment by results. Center for Health Economics Research Paper 19, The University of York.

Mullahy, J. (1998). Much ado about two: reconsidering retransformation and the two-part model in health econometrics. *Journal of Health Economics 17*(3), 247–281.

Mullahy, J. (2009). Econometric modeling of health care costs and expenditures: a survey of analytical issues and related policy considerations. *Medical Care 47*(7), S104–S108.

Munkin, M. K. and P. K. Trivedi (2010). Disentangling incentives effects of insurance coverage from adverse selection in the case of drug expenditure: a finite mixture approach. *Health Economics 19*(9), 1093–1108.

Muramatsu, N. and J. Liang (1996). Comparison of hospital length of stay and charges between Japan and the United States. In N. Ikegami and J. Campbell (Eds.), *Containing Healthcare Costs in Japan*, pp. 184–192. The University of Michigan Press.

National Institute of Population and Social Security Research (2005). Nihon shakai hoshou shiryou 1980-2000 (Materials on social security in Japan in 1980-2000).

Nawata, K. and K. Kawabuchi (2013). Evaluation of the DPC-based inclusive payment system in Japan for cataract operations by a new model. *Mathematics and Computers in Simulation 93*, 76–85.

Nawata, K., A. Nitta, S. Watanabe, and K. Kawabuchi (2006). An analysis of the length of stay and effectiveness of treatment for hip fracture patients in Japan: Evaluation of the 2002 revision of the medical service fee schedule. *Journal of Health Economics 25*(4), 722–739.

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

Newhouse, J. and D. Byrne (1988). Did Medicare's prospective payment system cause length of stay to fall? *Journal of Health Economics 7*, 413–416.

Newhouse, J. P. and C. E. Phelps (1976). New estimates of price and income elasticities of medical care services. In N. Rosett (Ed.), *The role of health insurance in the health services sector*, pp. 261–320. NBER.

Newhouse, J. P., C. E. Phelps, and M. S. Marquis (1980). On having your cake and eating it too: Econometric problems in estimating the demand for health services. *Journal of Econometrics 13*(3), 365–390.

Nishimura, S. (1987). *Iryou-no keizai bunseki [Economic Analysis of Healthcare].* Tokyo: Toyo keizai shimposha.

Nishioka, K. (2010). DPC-no kongo-no yukue. (Future development of DPCs). *ournal of Japan Hospital Association 6*, 18–45.

Okamura, S., R. Kobayashi, and T. Sakamaki (2005). Case-mix payment in Japanese medical care. *Health Policy 74*, 282–286.

Okuyama, T. (2008). An action of the DPC Support Tool project team in hospital of Sagamihara. *Journal of Japan Hospital Association 4*, 18–23.

Pauly, M. V. (1968). The economics of moral hazard: comment. *American Economic Review 58*, 531–537.

Phelps, C. and J. Newhouse (1974). Price and income elasticities for medical care services. Technical Report R-1197-NC/OEO, Rand.

Puig-Junoy, J., S. Rodriguez-Feijoo, and B. Lopez-Valcarcel (2013). Paying for formerly free medicines in spain: Dramatic prescription drops, looking for unanswered questions. Working paper 201307-76, CRES-UPF.

Reichmann, G. and M. Sommersguter-Reichmann (2004). Co-payments in the Austrian social health insurance system: Analysing patient behaviour and patients' views on the effects of co-payments. *Health Policy 67*(1), 75–91.

Rosenbaum, P. R. and D. B. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika 70*(1), 41–55.

Santos Silva, J. and F. Windmeijer (2001). Two-part multiple spell models for health care demand. *Journal of Econometrics 104*(1), 67–89.

Sarma, S. and W. Simpson (2006). A microeconometric analysis of Canadian health care utilization. *Health Economics 15*(3), 219–239.

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

Scalzo, A. L., A. Donatini, L. Orzella, A. Cicchetti, S. Profili, and A. Maresso (2009). Italy. Health System Review. *Health Systems in Transition 11*(6), 1–216.

Schmitz, H. (2012). More health care utilization with more insurance coverage? evidence from a latent class model with German data. *Applied Economics 44*(34), 4455–4468.

Schneeweiss, S., A. R. Patrick, M. Maclure, C. R. Dormuth, and R. J. Glynn (2007). Adherence to statin therapy under drug cost sharing in patients with and without acute myocardial infarction. A population-based natural experiment. *Circulation 115*(16), 2128–2135.

Schreyögg, J. and M. M. Grabka (2010). Copayments for ambulatory care in Germany: a natural experiment using a difference-in-difference approach. *The European Journal of Health Economics 11*(3), 331–341.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics 6*(2), 461–464.

Senoo, Y. (1985). Iryouhi yokoseisaku-no keizai bunseki [Economic analysis of healthcare cost containment]. In *Iryou sisutemu ron*, Tokyo, pp. 127–148. Toukyou daigaku shuppansha.

Shigeoka, H. (2014). The effect of patient cost sharing on utilization, health, and risk protection. *American Economic Review 104*(7), 2152–2184.

Tokita, T., K. Hosoya, Y. Hayashi, and H. Kumamoto (2002). A claim data analysis of medical fee revision. *Economic Review 53*(3), 226–235. (in Japanese).

Tokita, T., T. Yamada, K. Yamamoto, N. Izumida, and H. Konno (2000). A claim data analysis for Japanese medical demand and supply. *Economic Review 51*(4), 289–300. in Japanese.

Wedel, M. and W. DeSarbo (2002). Mixture regression models. In J. Hagenaars and A. McCutcheon (Eds.), *Applied Latent Class Analysis*, pp. 366–370. Cambridge University Press.

Wedel, M., W. S. DeSarbo, J. R. Bult, and V. Ramaswamy (1993). A latent class Poisson regression model for heterogeneous count data. *Journal of Applied Econometrics 8*(4), 397–411.

Welch, B. L., J. W. Hay, D. S. Miller, R. J. Olsen, R. M. Rippey, and A. S. Welch (1987). The Rand health insurance study: A summary critique. *Medical Care 25*(2), 148–156.

Westerhout, E. and K. Folmer (2013). Why it may hurt to be insured: The effects of capping coinsurance payments. Discussion Paper 239, CPB Netherlands Bureau for Economic Policy Analysis.

Winkelmann, R. (2004). Co-payments for prescription drugs and the demand for doctor visits–Evidence from a natural experiment. *Health Economics 13*(11), 1081–1089.

Winkelmann, R. (2006). Reforming healthcare: Evidence from quintile regressions for counts. *Journal of Health Economics 25*(1), 131–145.

Wouterse, B., M. Huisman, B. R. Meijboom, D. J. Deeg, and J. J. Polder (2013). Modeling the relationship between health and health care expenditures using a latent Markov model. *Journal of Health Economics 32*(2), 423–439.

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

Yamauchi, T. (1999). Healthcare system in Japan. *Nursing & Health Sciences 1*(1), 45–48.

Yasunaga, H., H. Ide, T. Imamura, and K. Ohe (2005a). Impacts of the Japanese diagnosis procedure combination based payment system on cardiovascular medicine-related costs. *International Heart Journal 46*, 855–866.

Yasunaga, H., H. Ide, T. Imamura, and K. Ohe (2005b). A proposal for reforms in the prospective payment system on DPC. *Hospital Administration 42*(2), 15–27.

Yasunaga, H., H. Ide, T. Imamura, and K. Ohe (2006). Influence of Japan's new diagnosis procedure combination-based payment system on the surgical sector: does it really shorten the hospital stay? *Surgery Today 36*(7), 577–585.

Yoshida, A. and S. Takagi (2002). Effects of the reform of the social medical insurance system in Japan. *Japanese Economic Review 53*(4), 444–465.

Tables

Table 1: **Health insurance plans for nonelderly consumers in Japan**

Name	**Enrollees**	**Share** enrollees	expenses	**Comments**
National health insurance	Self-employed, unemployed and their dependents, retirees	34.8%	58.4%	Managed by municipalities
Government-managed health insurance	Small firms employees and their dependents	31.0%	21.6%	Managed by the government
Company (society, association)-managed health insurance	Insurance societies formed by firms with over 300 employees for employees and their dependents	26.7%	15.2%	The number of societies has been gradually decreasing: from almost 2000 in 1999 (Ikegami and Campbell (1999) to 1,443 in 2012 (Ministry of Health, Labor and Welfare (2013a)).
Mutual-aid associations for national government employees	National government employees and dependents	2.1%	1.2%	20 associations for each ministry and agency (Ministry of Health, Labor and Welfare (2013a)). Decreased from 24 in 1995 to 20 in 2010 (Japan Statistical Yearbook (2013)).
Mutual-aid associations for local government employees	Local government employees and dependents	5.4%	3.5%	64 associations for local government employees (Ministry of Health, Labor and Welfare (2013a))
Seamen's insurance	Seamen and dependents	0.1%	0.1%	Managed by the government

Notes: Columns 3 and 4 present percentage shares of the plan in the total national figure of enrollment and expenditure (with exclusion of health insurance for the elderly) as of 2010 and 2009, respectively (computed according to Japan Statistical Yearbook (2013) and Ministry of Health, Labor and Welfare (2011). Owing to data availability 2009 and 2008 figures are used, correspondingly, for enrollment and healthcare expenditure in seamen insurance. Enrollment and expenditure in health insurance plan for the elderly (above 70) are not reported in the Table, owing to lower nominal coinsurance rates (see Shigeoka (2014) for details).

Table 2: **Coinsurance rates before and after April 2003 reform**

	Head of household		**Dependents**	
Health insurance plan	**before**	**after**	**before**	**after**
Company-managed insurance; Government-managed insurance; Seamen's insurance; Mutual-aid associations benefit schemes	20%	30%	30% outpatient care and drugs; 20% inpatient care	30%
National health insurance	30%	30%	30%	30%

Notes: The Table reports nominal coinsurance rates for enrollees aged 3-69. Nominal coinsurance rates are 0-20% for infants below 3 (may be extended to children below 15 in some municipalities); and 10-20% for the elderly (above 70).

Table 3: **Variable definition and summary statistics for JPSC sample in 2000-2010**

Variable	**Definition**	**Mean**	**St.dev.**	**Min**	**Max**
Dependent variable					
healthcare	unified fee schedule points, adjusted for insurance covered medical goods and services price index, in 2010 real terms	1836	2257	81.74	29822
Covariates					
income	total household before-tax income a year, thousand yen, adjusted for goods and services CPI, in 2010 real terms	7351	5501	49	63764
age	full years of age, as of March of the survey year	31.91	5.62	24	51
poor health	=1 if self-assessed health condition is reported as "not very healthy" or "not at all healthy"; 0 if self-assessed health condition is reported as "very healthy", "rather healthy" or "average health"	0.11	0.31	0	1
coinsurance	= 1 if nominal coinsurance rate for outpatient healthcare and insurance covered drugs is 30%; 0 otherwise	0.89	0.32	0	1
urban	= 1 if lives in city, 0 if lives in small towns or villages (*chouson*)	0.91	0.29	0	1
education	=1 if graduated from university, college or vocational school, 0 otherwise	0.58	0.49	0	1

Note: Number of observations in the unbalanced panel for 2000-2010 is 2203, number of individuals is 796. Healthcare shows expenditure in September of the survey year.

Table 4: **Residuals in the models for healthcare expenditure**

Residual		loglinear			Weibull			Exponential			Rayleigh	
	fmm-1	**fmm-2**	**fmm-3**	**fmm-1**	**fmm-2**	**fmm-3**	**fmm-1**	**fmm-2**	**fmm-3**	**fmm-1**	**fmm-2**	**fmm-3**
Whole sample												
bias	7.57	0.81	2.33	-11.44	107.53	99.11	-0.32	109.43	153.33	-646.32	-268.43	-158.04
	(2211.48)	(2041.92)	(2021.07)	(2210.02)	(2003.95)	(1995.25)	(2210.2)	(2005.23)	(1977.07)	(2228.78)	(2016.25)	(1918.93)
APE	1296.37	1085.62	1133.1	1305.52	1100.48	1079.8	1301.43	1170.1	1132.56	1591.75	1219.34	1083.43
	(1791.46)	(1729.33)	(1673.38)	(1783.3)	(1678.03)	(1680.58)	(1786.19)	(1631.67)	(1627.59)	(1688.37)	(1627.84)	(1591.52)
squared error	4888459	4167796	4082853	4883079	4025939	3989025	4882768	4030248	3930559	5382951	4135466	3705602
	(2.99E+07)	(2.78E+07)	(2.75E+07)	(2.96E+07)	(2.61E+07)	(2.60E+07)	(2.97E+07)	(2.44E+07)	(2.39E+07)	(2.68E+07)	(2.16E+07)	(1.97E+07)
Component 1												
raw bias		-9.52	-2.86		394.68	416.72		991.93	1387.79		-690.68	-718.99
		(2558.90)	(2611.77)		(3260.49)	(3464.19)		(4318.32)	(6525.31)		(3428.88)	(4212.55)
APE		1511.26	1727.44		2039.89	2242.45		2756.81	4434.63		2484.23	3082.57
		(2064.48)	(1955.77)		(2572.92)	(2671.71)		(3464.65)	(4952.63)		(2460.47)	(2955.35)
squared error		6542087	6793415		1.08E+07	1.22E+07		1.96E+07	4.38E+07		1.22E+07	1.82E+07
		(3.40E+07)	(2.32E+07)		(4.47E+07)	(4.75E+07)		(6.12E+07)	(1.00E+08)		(3.89E+07)	(4.69E+07)
Component 2												
raw bias		11.13	2.40		-34.19	-23.07		-1.44	935.05		-97.05	-65.03
		(1342.19)	(2015.55)		(833.72)	(901.48)		(1469.72)	(3016.70)		(920.34)	(536.03)
APE		661.13	1131.15		636.82	687.45		978.82	2030.39		705.96	391.87
		(1167.95)	(1668.01)		(538.93)	(583.31)		(1096.13)	(2416.75)		(598.13)	(371.22)
squared error		1799963	4060199		695781.2	812566.7		2158974	9942283		855910.9	291179.6
		(1.96E+07)	(2.92E+07)		(1469576)	(2019971)		(1.36E+07)	(3.14E+07)		(2064757)	(872429.3)
Component 3												
raw bias			9.62			-57.05			-2.42			-46.75
			(325.07)			(357.93)			(1337.88)			(1235.63)
APE			226.04			259.60			895.08			936.41
			(233.12)			(252.50)			(994.15)			(807.03)
squared error			105088.8			130918.4			1788972			1527578
			(287059)			(409154.5)			(1.28E+07)			(3284025)

Notes: "fmm-1", "fmm-2 " and "fmm-3 " denote, respectively, models with one component (deterministic model without latent classes), with two components and with three components. "APE" is absolute prediction error. Each cell shows the mean value of corresponding residual and standard deviation in parentheses. GLM models with inverse Gaussian distribution family and gamma distribution family did not converge.

Table 5: **Goodness of fit in the models for healthcare expenditure**

Statistics		**loglinear**			**Weibull**	
	fmm-1	**fmm-2**	**fmm-3**	**fmm-1**	**fmm-2**	**fmm-3**
ln L	-2923.41	-2866.82	-2841.95	-18684.49	-18543.03	-18494.39
AIC	2941.41	2900.82	2893.95	18700.49	18577.03	18546.39
Andrews (1988) χ^2	1247.62	1153.06	1689.25	1991.78	68.48	91.05
parameters	9	17	26	8	17	26

Notes: "fmm-1", "fmm-2 " and "fmm-3 " denote, respectively, models with one, two and three components. $AIC = -lnL + 2 * k$, where k is the number of parameters.

Table 6: **Marginal effects in the models for healthcare expenditure**

		loglinear				**Weibull**			
		fmm-2		**fmm-3**		**fmm-2**		**fmm-3**	
component 1	constant	16506.58***	(1358.84)	30209.29***	(3806.42)	18961.49***	(5323.51)	19265.89***	(5652.23)
	log income	63.45	(107.88)	-545.11**	(280.16)	51.91	(127.04)	51.66	(139.29)
	age	53.75***	(10.90)	75.60***	(22.77)	79.70***	(27.30)	81.89***	(29.87)
	poor health	1621.64	(1586.15)	2709.11	(4656.24)	1416.88**	(559.64)	1408.78**	(599.77)
	coinsurance	-1064.63	(926.87)	-3275.63	(2345.42)	-907.96*	(485.23)	-802.43	(501.53)
	urban	-400.17	(1054.17)	-32.59	(2741.47)	-557.81	(410.57)	-452.19	(463.58)
	education	195.80	(1030.51)	72.08	(2725.00)	411.42	(218.79)	415.89**	(235.86)
component 2	constant	5907.01***	(580.60)	9306.32***	(781.11)	7059.18***	(1629.21)	8883.95***	(2565.99)
	log income	102.778***	(42.21)	196.86***	(57.60)	137.48***	(52.16)	181.61**	(74.70)
	age	26.43***	(6.73)	32.29***	(7.57)	25.67***	(7.72)	26.22***	(9.35)
	poor health	396.33	(545.84)	348.44	(661.55)	433.68***	(156.04)	269.79*	(161.47)
	coinsurance	-367.58	(400.61)	-496.01	(549.64)	-803.69***	(238.23)	-923.39***	(328.57)
	urban	-104.03	(420.28)	-94.76	(578.60)	-145.45	(117.27)	-498.72**	(242.89)
	education	40.56	(417.58)	29.00	(564.71)	68.04	(72.11)	-63.97	(79.92)
component 3	constant			2527.50***	(555.54)			3639.58**	(1637.48)
	log income			19.68	(42.07)			28.77	(44.05)
	age			14.07*	(8.04)			9.97	(6.79)
	poor health			853.39	(1109.61)			1131.36*	(647.47)
	coinsurance			-226.90	(394.72)			-371.98*	(225.30)
	urban			-158.59	(414.48)			-240.97*	(148.29)
	education			9.45	(408.12)			51.25	(63.44)
mixing proportion π_j (prior probability)	component 1	0.4822***	(0.0534)	0.1547***	(0.0352)	0.4001***	(0.0380)	0.3569***	(0.0347)
	component 2	0.5178***	(0.0534)	0.7542***	(0.0393)	0.5999***	(0.0380)	0.5021***	(0.0381)
	component 3			0.0911***	(0.0219)			0.1409***	(0.0239)
Shape parameter	component 1					1.0849***	(0.0307)	1.0622***	(0.0311)
	component 2					1.5302***	(0.0424)	1.668***	(0.0553)
	component 3							1.9350***	(0.1074)

Notes: Dependent variable is log(healthcare) in loglinear model and healthcare in generalized linear model (with log link function and Weibull distribution family). For each model the Table presents marginal effects for covariates of healthcare and robust standard errors (evaluated at sample means using delta method), along with coefficients for variables explaining component membership. Time dummies proved insignificant and are excluded from the list of covariates. "fmm-2 " and "fmm-3 " denote, respectively, models with two and three components. Components 1 and 2 in fmm-2 denote high and low expenses. Components 1, 2 and 3 in fmm-3 indicate high, medium and low expenses.

Table 7: **Posterior probability of component membership**

	fmm-2, component 1		**fmm-3, component 1**		**fmm-3, component 2**	
	loglinear	**Weibull**	**loglinear**	**Weibull**	**loglinear**	**Weibull**
age	-0.045***	-0.055***	-0.294***	-0.290***	-0.026***	-0.022***
	(0.008)	(0.007)	(0.028)	(0.027)	(0.006)	(0.007)
log income	0.189***	0.084**	1.411***	1.389***	0.005	-0.017
	(0.058)	(0.042)	(0.180)	(0.179)	(0.030)	(0.038)
health condition: good	-0.085	0.174*	-0.480	-0.485	-0.036	-0.041
	(0.139)	(0.098)	(0.435)	(0.434)	(0.052)	(0.071)
health condition: average	0.184	0.351***	0.548	0.536	-0.094	-0.106
	(0.143)	(0.103)	(0.450)	(0.447)	(0.06)1	(0.087)
health condition: poor	-0.374**	-0.046	-1.424**	-1.450**	-0.156	-0.182
	(0.177)	(0.144)	(0.587)	(0.579)	(0.111)	(0.134)
health condition: very poor	0.441**	0.352*	0.517	0.679	0.249***	0.411***
	(0.205)	(0.211)	(0.724)	(0.689)	(0.096)	(0.156)
education	-0.212**	-0.337***	0.034	0.052	0.015	0.033
	(0.089)	(0.066)	(0.283)	(0.280)	(0.057)	(0.068)
urban	0.319**	0.209*	-0.386	-0.305	0.077	0.159*
	(0.153)	(0.112)	(0.412)	(0.401)	(0.060)	(0.083)
constant	-1.879***	-0.739*	-8.546***	-7.649***	0.255	-0.092
	(0.578)	(0.440)	(1.835)	(1.813)	(0.314)	(0.398)

Notes: "fmm-2 " and "fmm-3 " denote, respectively, models with two and three components. Robust standard errors in parentheses. Components 1 and 2 in fmm-2 denote subpopulations with high and low expenditure. Components 1, 2 and 3 in fmm-3 indicate subpopulations with high, medium and low expenditure. The analysis uses binary variables, reflecting the original five-point scale of self-assessed health. "Excellent health" is a reference category.

Table 8: **Preferred percentage of the model with 3 components in crossvalidation**

	Statistics		**loglinear**	**Weibull**
Training sample	ln L	over fmm-1	100	100
		over fmm-2	100	100
	AIC	over fmm-1	0	100
		over fmm-2	90	100
	Andrews (1988) χ^2	over fmm-1	100	100
		over fmm-2	48	26
Holdout sample	ln L	over fmm-1	4	100
		over fmm-2	28	86
	AIC	over fmm-1	0	50
		over fmm-2	0	2
	Andrews (1988) χ^2	over fmm-1	100	90
		over fmm-2	40	48

Notes: Preferred percentage shows percentage of cases when the three component loglinear (or Weibull glm) model is preferred to the corresponding one-component or two-component model ("fmm-1" or "fmm-2", respectively). The estimations are based on 50 simulations, with 80% of respondents constructing training sample and 20% being a holdout sample. $AIC = -lnL + 2 * k$, where k is the number of parameters.

Table 9: **Difference in loglikelihood in crossvalidation**

	Statistics		**loglinear**	**Weibull**
Training sample	$lnL_{\text{fmm-3}} - lnL_{\text{fmm-1}}$	mean	19.29	152.52
		min	8.95	136.51
		max	33.10	177.36

Table 9: **Difference in loglikelihood in crossvalidation**

	Statistics		loglinear	Weibull
	$lnL_{\text{fmm-3}} - lnL_{\text{fmm-2}}$	mean	22.74	38.55
		min	14.06	26.69
		max	32.25	50.04
Holdout sample	$lnL_{\text{fmm-3}} - lnL_{\text{fmm-1}}$	mean	-8.99	32.35
		min	-26.83	10.53
		max	1.15	48.20
	$lnL_{\text{fmm-3}} - lnL_{\text{fmm-2}}$	mean	-1.99	5.89
		min	-18.98	-3.44
		max	6.75	19.84

Notes: The estimations are based on 50 simulations, with 80% of respondents constructing training sample and 20% beeing a holdout sample. "fmm-1", "fmm-2 " and "fmm-3" denote, respectively, models with one component (deterministic model without latent classes), with two and three components. Mean, min and max summarize distribution of the corresponding difference between loglikelihood values of "fmm-3" and "fmm-1" (or "fmm-2") across simulations.

Table 10: **Average treatment effect in each subpopulation**

	loglinear				**Weibull**			
	component 1		**component 2**		**component 1**		**component 2**	
ATE	-542.01***	(77.56)	-432.33***	(55.85)	-652.03***	(105.76)	-607.24***	(63.07)
Linear CATE	-521.37***	(69.91)	-425.44***	(51.43)	-619.16***	(98.05)	-589.64***	(57.31)
Nonlinear CATE								
$m = 1$	-685.04	(697.00)	-446.65	(453.32)	-931.25	(848.40)	-618.43	(501.21)
$m = 2$	-660.60	(547.03)	-426.15	(392.96)	-847.24	(672.73)	-605.59	(419.79)
$m = 3$	-676.98	(540.37)	-432.85	(404.38)	-882.21	(687.06)	-607.82	(408.20)
Distance								
$m = 1$	0.8185	(0.7734)	0.8421	(0.6958)	0.8071	(0.7415)	0.8418	(0.7335)
$m = 2$	0.9829	(0.8384)	1.0255	(0.8045)	1.0165	(0.8369)	0.9975	(0.8147)
$m = 3$	1.0933	(0.8690)	1.1279	(0.8507)	1.1405	(0.8872)	1.0951	(0.8460)
Observations	65		63		43		85	

Note: The dependent variable is the difference in the fitted values of mean post- and pre-reform healthcare expenditure. Matching variables and variables for bias correction in the estimation of conditional average treatment effect are logarithm of CPI adjusted household income, age (mean values in the pre-reform period), binary variables for higher education and urban residence (the value as of 2003 or the closest earlier year available). Exact matching is conducted according to the variable "poor health" (the value as of 2003 or the closest earlier year available). $m = 1, ..., 3$ indicates the number of matches. Owing to impossibility of exact match, distance increases appreciably with $m = 4$, so $m = 3$ becomes the largest possible number of potential matches in the analysis. Robust standard errors in parentheses for linear estimators, standard deviation - for distance and nonlinear CATE.

Table 11: **Marginal effects for consumers of age 24-51 in JPSC and JHPS**

	loglinear								Weibull							
	JPSC, fmm-2		JHPS, fmm-2		JPSC, fmm-3		JHPS, fmm-3		JPSC, fmm-2		JHPS, fmm-2		JPSC, fmm-3		JHPS, fmm-3	
Component 1																
constant	14287.14***	(1316.28)	6879.85***	(521.82)	27023.60***	(2828.57)	15852.82***	(2482.09)	17476.13***	(5187.26)	14792.17***	(4695.56)	17799.30***	(5296.66)	18997.15**	(7656.68)
log income	101.22	(108.74)	108.97**	(43.30)	-540.80**	(220.27)	417.85*	(230.51)	60.76	(126.25)	-18.30	(127.21)	68.71	(133.37)	-71.51	(192.26)
age	48.12***	(10.95)	30.34***	(4.48)	-131.77***	(24.07)	109.25***	(30.61)	69.86***	(26.49)	63.74***	(24.13)	67.72**	(26.78)	83.72**	(38.40)
poor health	1236.12	(1438.91)	930.08	(591.73)	581.83	(2261.18)	1661.65	(2903.11)	1144.15**	(511.94)	1558.38**	(671.31)	1108.00**	(516.47)	1954.91*	(1067.53)
education	107.27	(1014.45)	-1.56	(361.47)	564.25	(2135.48)	-2.05	(2045.77)	279.57	(209.84)	203.26	(234.26)	253.26	(215.85)	311.74	(366.54)
Component 2																
constant	4901.78***	(558.19)	1532.22***	(139.61)	8448.73***	(833.69)	5231.41***	(392.63)	5388.40***	(1300.58)	2874.63***	(512.27)	6358.39***	(2046.81)	4407.89***	(1247.86)
log income	104.18**	(43.38)	16.70	(14.59)	230.33***	(63.85)	-12.31	(36.89)	164.74***	(56.72)	2.09	(20.10)	210.69**	(85.02)	22.09	(27.52)
age	26.77***	(7.00)	4.91***	(1.12)	56.79***	(7.13)	12.10***	(3.29)	26.00***	(7.74)	5.02***	(1.86)	26.07***	(9.81)	9.82***	(3.81)
poor health	370.21	(563.87)	332.04	(216.64)	422.74	(754.98)	653.34	(516.93)	399.90***	(144.01)	457.28***	(102.67)	236.27	(169.20)	608.65***	(201.58)
education	72.24	(438.94)	39.39	(122.96)	37.60	(630.63)	62.35	(319.25)	77.95	(64.40)	22.88	(25.08)	30.33	(74.50)	30.50	(40.87)
Component 3																
constant					1981.65***	(532.83)	1176.29***	(109.08)					2546.23***	(1244.88)	1108.06***	(318.48)
log income					31.52	(45.25)	9.14	(11.70)					51.69	(50.84)	2.98	(7.92)
age					17.55**	(6.91)	3.79***	(0.93)					15.37*	(9.08)	3.42**	(1.48)
poor health					643.95	(954.41)	243.03	(170.92)					1062.74	(745.33)	278.73***	(100.70)
education					53.83	(443.30)	35.59	(100.30)					94.06	(79.08)	21.78	(13.53)
Mixing proportion π_j *(prior probability)*																
component 1	0.5023***	(0.0621)	0.5169***	(0.0275)	0.1049***	(0.0284)	0.1898***	(0.0298)	0.4103***	(0.0364)	0.2519***	(0.0278)	0.3877***	(0.0351)	0.1721***	(0.0190)
component 2	0.4977***	(0.0621)	0.4831***	(0.0275)	0.7864***	(0.0361)	0.3644***	(0.0377)	0.5897***	(0.0364)	0.7481***	(0.0278)	0.4807***	(0.0396)	0.5055***	(0.0264)
component 3					0.1085***	(0.0269)	0.4426***	(0.0248)					0.1316***	(0.0250)	0.3225***	(0.0221)
Shape parameter																
component 1									1.1164***	(0.0335)	0.9341***	(0.0283)	1.1050***	(0.0333)	0.9196***	(0.0347)
component 2									1.5595***	(0.0446)	1.3359***	(0.0323)	1.7290***	(0.0648)	1.5830***	(0.0557)
component 3													1.9228***	(0.1191)	1.9571***	(0.0876)

Notes: Dependent variable is log(healthcare) in loglinear model and healthcare in generalized linear model (with log link function and Weibull distribution family). For each model the Table presents marginal effects for covariates of healthcare and robust standard errors (evaluated at sample means using delta method), along with coefficients for variables explaining component membership. Time dummies proved insignificant and are excluded from the list of covariates. “fmm-2 ” and “fmm-3 ” denote, respectively, models with two and three components. Components 1 and 2 in fmm-2 denote high and low expenses. Components 1, 2 and 3 in fmm-3 indicate high, medium and low expenses.

Table 12: **Marginal effects for nonelderly consumers in JHPS**

	loglinear								Weibull							
	young, fmm-2		all, fmm-2		young, fmm-3		all, fmm-3		young, fmm-2		all, fmm-2		young, fmm-3		all, fmm-3	
Component 1																
constant	6419.99***	(528.59)	8648.31***	(434.71)	12626.48***	(2419.29)	18146.96***	(2135.77)	14261.99***	(4734.72)	17787.63***	(4717.87)	17604.85**	(7094.51)	21614.13***	(7279.01)
log income	108.13**	(42.30)	169.27***	(35.44)	497.63**	(223.02)	773.49***	(185.10)	-43.35	(129.42)	312.06**	(136.55)	-101.50	(184.79)	347.66*	(195.62)
age	32.05***	(5.00)	44.05***	(2.89)	141.51***	(40.13)	105.38***	(17.52)	68.58**	(27.22)	67.10***	(19.15)	86.38**	(39.31)	77.68***	(29.27)
poor health	841.56	(578.42)	991.30**	(464.38)	1511.23	(2869.29)	1419.30	(2118.35)	1640.01**	(731.36)	1044.69**	(460.18)	2024.93*	(1107.27)	1065.04	(667.08)
education	5.24	(365.17)	-7.00	(310.05)	391.41	(2180.45)	228.18	(1700.87)	277.30	(245.09)	236.95	(243.33)	345.09	(346.15)	289.31	(362.00)
unmarried	-88.50	(333.78)	-116.47	(284.22)	149.65	(2046.20)	195.40	(1625.18)	-483.88	(332.13)	-479.29	(310.52)	-628.02	(477.88)	-601.87	(461.46)
nochild	332.18	(422.16)	415.32	(345.12)	1077.93	(2464.87)	898.14	(1836.77)	1152.27**	(488.18)	1166.69***	(395.17)	1504.31**	(729.11)	1462.41**	(600.27)
female	131.18	(379.00)	-0.84	(306.62)	1239.33	(2403.80)	631.10	(1741.42)	536.55*	(281.00)	436.86*	(250.81)	748.83*	(416.85)	480.55	(360.95)
Component 2																
constant	1557.11***	(154.63)	2005.72***	(158.69)	5169.92***	(405.67)	6931.94***	(324.33)	2877.33***	(485.60)	3936.24***	(513.75)	4285.92***	(1162.90)	5220.60***	(1065.82)
log income	11.64	(15.36)	15.04	(14.16)	-21.84	(36.08)	-38.37	(29.64)	-1.15	(19.35)	-0.52	(17.17)	18.67	(26.05)	5.59	(22.94)
age	4.70***	(1.22)	11.66***	(1.00)	10.43***	(3.48)	31.81***	(1.89)	5.31***	(1.86)	20.10***	(2.74)	10.19***	(3.82)	26.90***	(5.56)
poor health	330.07	(238.46)	463.35**	(233.30)	600.79	(501.00)	728.79*	(392.54)	430.54***	(94.15)	606.97***	(96.59)	580.03***	(183.02)	663.52***	(153.54)
education	41.08	(134.43)	29.77	(129.07)	50.65	(313.77)	-72.67	(246.16)	21.64	(24.85)	-25.64	(25.37)	8.94	(37.38)	-8.13	(35.40)
unmarried	-46.93	(109.44)	-29.72	(113.61)	-87.99	(272.52)	-214.09	(213.26)	-37.11	(33.77)	-100.35***	(25.37)	-52.88	(54.53)	-687.57***	(152.09)
nochild	49.18	(138.89)	109.15	(136.84)	188.59	(347.19)	306.35	(284.23)	133.72***	(38.91)	240.42***	(41.48)	164.61**	(66.57)	191.14***	(56.62)
female	-21.22	(122.89)	-36.05	(118.86)	-52.27	(290.75)	-128.51	(239.25)	-12.43	(24.43)	-61.92***	(25.04)	8.22	(36.84)	-94.61**	(37.58)
Component 3																
constant					1214.09***	(124.56)	1829.54***	(138.80)					1133.14***	(349.08)	2247.77***	(454.73)
log income					3.67	(12.72)	8.34	(12.76)					0.00	(8.29)	5.03	(15.09)
age					3.25***	(1.01)	10.38***	(0.88)					3.10**	(1.40)	14.16***	(3.01)
poor health					231.93	(190.14)	387.14**	(203.69)					282.09***	(106.94)	434.10***	(107.79)
education					36.85	(112.62)	12.03	(113.88)					21.48	(13.61)	16.03	(25.19)
unmarried					-44.71	(88.26)	-34.13	(100.66)					-28.55	(20.83)	787.70***	(206.39)
nochild					34.18	(114.44)	92.89	(122.60)					14.02	(17.22)	129.36***	(37.35)
female					-14.13	(102.28)	-36.19	(106.26)					-1.54	(14.10)	-56.04**	(26.16)
Mixing proportion π_j *(prior probability)*																
component 1	0.5243***	(0.0276)	0.5353***	(0.0214)	0.1941***	(0.0280)	0.1919***	(0.0176)	0.2465***	(0.0252)	0.2166***	(0.0164)	0.1778***	(0.0177)	0.1519***	(0.0128)
component 2	0.4757***	(0.0276)	0.4647***	(0.0214)	0.3802***	(0.0360)	0.3410***	(0.0225)	0.7535***	(0.0252)	0.7834***	(0.0164)	0.5045***	(0.0262)	0.4816***	(0.0234)
component 3					0.4257***	(0.0253)	0.4672***	(0.0179)					0.3177***	(0.0229)	0.3664***	(0.0229)
Shape parameter																
component 1									0.9606***	(0.0302)	0.9638***	(0.0239)	0.9480***	(0.0357)	0.9145***	(0.0284)
component 2									1.3385***	(0.0303)	1.3543***	(0.0205)	1.6054***	(0.0533)	1.7136***	(0.0417)
component 3													1.9734***	(0.0956)	1.6633***	(0.0459)

Notes: Dependent variable is log(healthcare) in loglinear model and healthcare in generalized linear model (with log link function and Weibull distribution family). For each model the Table presents marginal effects for covariates of healthcare and robust standard errors (evaluated at sample means using delta method), along with coefficients for variables explaining component membership. "young" denotes subgroup of age 24-51, "all" indicates all nonelderly consumers. Time dummies proved insignificant and are excluded from the list of covariates. "fmm-2 " and "fmm-3 " denote, respectively, models with two and three components. Components 1 and 2 in fmm-2 denote high and low expenses. Components 1, 2 and 3 in fmm-3 indicate high, medium and low expenses.

Table 13: **Posterior probability of belonging to the component with the highest healthcare expenditure**

	young, fmm-2		**young, fmm-3**		**all, fmm-2**		**all, fmm-3**	
	loglinear	Weibull	loglinear	Weibull	loglinear	Weibull	loglinear	Weibull
age	-0.040***	-0.036***	-0.089***	-0.087***	-0.012***	-0.005**	-0.015***	-0.015***
	(0.005)	(0.004)	(0.007)	(0.007)	(0.003)	(0.002)	(0.003)	(0.003)
log income	-0.043	0.106**	-0.122	-0.124*	-0.092**	-0.043	-0.240***	-0.233***
	(0.055)	(0.044)	(0.075)	(0.072)	(0.042)	(0.029)	(0.046)	(0.045)
health condition: fairly good	0.434***	0.233***	0.612***	0.572***	0.395***	0.149***	0.386***	0.351***
	(0.098)	(0.077)	(0.134)	(0.128)	(0.087)	(0.057)	(0.094)	(0.091)
health condition: average	0.427***	0.300***	0.595***	0.555***	0.554***	0.201***	0.529***	0.475***
	(0.104)	(0.080)	(0.141)	(0.135)	(0.085)	(0.056)	(0.092)	(0.089)
health condition: fairly bad	0.849***	0.488***	1.436***	1.380***	0.942***	0.567***	1.197***	1.141***
	(0.135)	(0.126)	(0.186)	(0.178)	(0.109)	(0.078)	(0.118)	(0.115)
health condition: bad	1.189***	0.954***	1.920***	1.840***	0.913***	1.053***	1.334***	1.260***
	(0.241)	(0.278)	(0.317)	(0.305)	(0.263)	(0.162)	(0.248)	(0.240)
education	-0.036	-0.224***	-0.334***	-0.322***	-0.157**	-0.217***	-0.372***	-0.375***
	(0.071)	(0.059)	(0.096)	(0.092)	(0.063)	(0.043)	(0.068)	(0.066)
overweight	0.368***	0.334***	0.748***	0.734***	0.338***	0.188***	0.367***	0.352***
	(0.090)	(0.081)	(0.125)	(0.119)	(0.072)	(0.056)	(0.080)	(0.078)
obese	0.803***	1.031***	1.602***	1.574***	0.730***	0.764***	1.058***	1.056***
	(0.166)	(0.158)	(0.242)	(0.238)	(0.140)	(0.119)	(0.167)	(0.168)
checkup	0.296***	0.166***	0.383***	0.357***	0.360***	0.101**	0.331***	0.304***
	(0.074)	(0.062)	(0.102)	(0.098)	(0.062)	(0.042)	(0.067)	(0.065)
smokes	0.078	0.165**	0.339***	0.346***	0.064	0.119**	0.117	0.107
	(0.076)	(0.065)	(0.100)	(0.095)	(0.069)	(0.048)	(0.073)	(0.071)
drinks	0.331***	0.151**	0.538***	0.515***	0.003	-0.0366	-0.0376	-0.035
	(0.078)	(0.068)	(0.105)	(0.100)	(0.069)	(0.047)	(0.073)	(0.071)
PDI	0.011**	0.021***	0.034***	0.0347***	0.008*	0.010***	0.0127**	0.013***
	(0.006)	(0.005)	(0.008)	(0.007)	(0.005)	(0.00322	(0.005)	(0.005)
gym	0.120	0.080	0.071	0.057	0.053	0.059	0.071	0.065
	(0.074)	(0.061)	(0.102)	(0.098)	(0.062)	(0.042)	(0.067)	(0.065)
nochild	-0.024	-0.202**	-0.196	-0.215	0.254***	-0.021	0.291***	0.256***
	(0.101)	(0.085)	(0.144)	(0.139)	(0.081)	(0.056)	(0.090)	(0.087)
nonmarried	0.051	0.139	-0.188	-0.205	-0.035	0.044	-0.251***	-0.246***
	(0.112)	(0.094)	(0.155)	(0.149)	(0.086)	(0.060)	(0.097)	(0.095)
female	-0.360***	-0.324***	-1.064***	-1.055***	-0.236***	-0.268***	-0.585***	-0.575***
	(0.078)	(0.066)	(0.105)	(0.100)	(0.065)	(0.046)	(0.071)	(0.069)
Constant	-0.559	-2.993***	-0.770	-0.886	-1.022**	-2.315***	-1.022**	-1.233***
	(0.487)	(0.404)	(0.660)	(0.630)	(0.424)	(0.296)	(0.458)	(0.446)
Observations	2,615	2,615	2,615	2,615	5,022	5,022	5,022	5,022
R-squared	0.056	0.067	0.116	0.121	0.039	0.044	0.066	0.065

Notes: “fmm-2 ” and “fmm-3 ” denote, respectively, models with two and three components. “young” denotes subgroup of JHPS consumers of age 24-51, “all” indicates all nonelderly consumers of JHPS. The analysis uses binary variables, reflecting the original five-point scale of self-assessed health, with top category “good” as a reference category.

Table 14: **Variable definition and descriptive statistics for unbalanced panels**

Variable	**Definition**	**JPSC**				**JHPS, young**				**JHPS, all**			
		Mean	St.dev.	Min	Max	Mean	St.dev.	Min	Max	Mean	St.dev.	Min	Max
healthcare	average unified fee schedule points a month, adjusted for insurance covered medical goods and services price index, in 2010 real terms	1743.65	2060.95	81.74	28821.69	992.56	2089.84	27.74	44608.86	1417.90	2690.81	27.74	59305.55
income	total household before-tax income a year, thousand yen , adjusted for goods and services CPI, in 2010 real terms	7303.44	5478.47	48.97	63763.66	6980.09	4120.70	19.59	68560.20	6885.49	4804.08	19.59	90000.02
age	full years of age	31.8	5.88	24	51	38.24	7.68	24	51	47.73	14.04	19	69
poor health	=1 if self-assessed health condition is reported as "not very healthy (fairly bad)" or "not at all healthy (bad)"	0.11	0.32	0	1	0.10	0.29	0	1	0.11	0.31	0	1
education	=1 if graduated from university, college or vocational school	0.57	0.49	0	1	0.52	0.50	0	1	0.44	0.50	0	1
nochild	=1 if no children (no children less than 20 years old for JHPS)					0.39	0.49	0	1	0.66	0.47	0	1
unmarried	=1 if unmarried					0.26	0.44	0	1	0.24	0.43	0	1
female	=1 if female					0.53	0.50	0	1	0.53	0.50	0	1
obese	= 1 if body mass index is greater or equal to 30					0.04	0.20	0	1	0.03	0.17	0	1
overweight	=1 if body mass index in the range of [25,30)					0.16	0.36	0	1	0.17	0.37	0	1
PDI	physiological distress index					33.39	7.28	12	48	34.01	7.11	12	48
checkup	= 1 if had nonnegative expenditure for checkups, apart from checkups at work					0.40	0.49	0	1	0.45	0.50	0	1
gym	= 1 if had nonnegative expenditure for doing sports, going to gym or buying supplements					0.40	0.49	0	1	0.40	0.49	0	1
smokes	= 1 if currently smokes					0.26	0.44	0	1	0.22	0.42	0	1
drinks	= 1 if drinks heavily (three times or more per week)					0.26	0.44	0	1	0.27	0.44	0	1

Notes: Number of observations in the unbalanced panels are 1863 in case of JPSC (2003-2010); 2716 for JHPS "young" respondents, i.e. aged 24-51 (2008-2010), and 5292 for all nonelderly respondents in JHPS (2008-2010). Physiological distress index is the sum of responses to questions on the presence of twelve conditions: *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*. Each response is given on a four-point scale: 1 - "often", 2 - "sometimes", 3- "almost never", 4 - "never". Body mass index (bmi) is computed as weight in kilograms divided by squared height in meters.