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International Journal of Health Economics and Management

ISSN 2199-9023

Int J Health Econ Manag.
DOI 10.1007/s10754-018-9246-z

Springer

Int J Health Econ Manag.
https://doi.org/10.1007/s10754-018-9246-z

RESEARCH ARTICLE

Estimating asymmetric information effects in health care with uninsurable costs

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Received: 11 September 2016 / Accepted: 5 July 2018

Abstract
We use a structural approach to separately estimate moral hazard and adverse selection effects in health care utilization using hospital invoices data. Our model explicitly accounts for the heterogeneity in the non-insurable transactions costs associated with hospital visits which increase the individuals' total cost of health care and dampen the moral hazard effect. A measure of moral hazard is derived as the difference between the observed and the counterfactual health care consumption. In the population of patients with non life-threatening diagnoses, our results indicate statistically significant and economically meaningful moral hazard. We also test for the presence of adverse selection by investigating whether patients with different health status sort themselves into different health insurance plans. Adverse selection is confirmed in the data because patients with estimated worse health tend to buy the insurance coverage and patients with estimated better health choose not to buy the insurance coverage.

Keywords Moral hazard · Adverse selection · Health insurance · Transaction costs

JEL Classification C14 · D82 · I11

Introduction

The empirical literature dealing with the estimation of moral hazard and adverse selection effects in health care utilization is quite large. For example, Manning et al. (1987) used a

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Published online: 14 July 2018

randomized experiment and found that a catastrophic insurance plan reduces expenditures 31 percent relative to zero out-of-pocket price, indicating a large moral hazard effect. Using the British Household Panel Survey, Olivella and Vera-Hernandez (2013) found that adverse selection is present in the private health insurance market. Individuals who purchase private health insurance (PHI) have a higher probability of both hospitalisation and visiting their general practitioner than individuals who receive PHI as a fringe benefit from employers. Fewer studies succeeded in disentangling these two effects. For example, Wolfe and Goddeeris (1991) estimated adverse selection as the effect of lag health status or lag health expenditure on current insurance decisions in a longitudinal study of Medigap insurance. They found a nontrivial decrease in moral hazard after taking into account the adverse selection. Liu et al. (2012) successfully disentangled moral hazard from adverse selection, taking advantage of the unique features of health care system in Croatia. Using matching estimators, they discovered favorable selection effect for patients in the 20–30 year cohort, adverse selection for patients in older age cohorts and significant moral hazard for all age cohorts.

In this paper we rely on the structural approach to estimate the effects of moral hazard and adverse selection using the hospital invoices data for non life-threatening diagnoses. The data covers a four-month period in 2009 of all outpatient services provided to local patients by a small regional hospital in Croatia. Croatia has a government controlled health care system with a single payer insurance fund. The main contribution of this paper is seen in the modeling and estimation approach which explicitly accounts for the heterogeneity in the non-insurable transactions costs associated with hospital visit over and above the direct health care expenses. By transactions costs we mean lost wages due to absenteeism from work, transportation costs, hiring an escort or a babysitter, etc. We found that these transaction costs are large and increase the individuals' total cost of health care significantly.

Structural estimation of adverse selection and moral hazard has also been used in the health insurance literature before. Earlier work was based on constructing health care demand, using price elasticities as the measure of moral hazard, and the unexplained correlation between insurance and health care demand as the measure of adverse selection. Cameron et al. (1988) derived closed form demand functions for health insurance and health care for a risk-averse consumer under uncertainty. Using data from 1977–1978 Australian Health Survey, they found a statistical dependence between error terms of health insurance and health care demand equations which suggest the presence of adverse selection. They also found a significant price effect in health care consumption which identifies the moral hazard as an important determinant of the overall health care utilization. Cardon and Hendel (2001) integrated health insurance and health care demand using 1987 National Medical Expenditure Survey data. Their objective was to estimate whether consumers' private information is an important link between insurance and health care demand. They did not find any evidence of adverse selection but found that the gap in expenditure between insured and uninsured can be attributed to observable demographic differences and to price sensitivity. They concluded that this price elasticity to coinsurance rate is an evidence of moral hazard. Vera-Hernandez (2003) introduced a new measure of moral hazard based on the conditional correlation between contractible (treatment cost) and non-contractible (health shocks) variables. If this correlation is zero, the relationship between the health shocks and treatment costs would be deterministic and then there would be no moral hazard. Using RAND Health Insurance Experiment data and simulated maximum likelihood estimator, the author uncovered the structural model parameters. The results reject the nonexistence of moral hazard at 95% confidence level with about two-thirds of the variance of residual health shock explained by the cost and one third left unexplained, a measure of moral hazard. Gardiol et al. (2005) developed a structural model of joint demand for health insurance and health care. They took advantage of the design feature of the Swiss insurance system where consumers choose their coverage from a menu of insurance plans ranked by the size of their deductibles. They used insurance claims data and found evidence of both selection and moral hazard effects. Their results indicate that 75% of the correlation between insurance coverage and health care expenditures may be attributed to selection and 25% to ex post moral hazard.

The most closely related to our paper is Bajari et al. (2014). They proposed a two-step semiparametric estimation strategy to disentangle the adverse selection and moral hazard effects in medical care. They used a unique claims data from a large self-insured employer in the U.S. In the theoretical model, they introduced the latent health status parameter into the utility function and used the GMM approach to estimate it. Moral hazard is then estimated as the difference between health care consumption of people with the insurance and their counterfactual consumption with no coverage. Adverse selection is examined by comparing health status distributions of people in different insurance plan groups. The fact that people with worse latent health status sort themselves into insurance plan with higher coverage is an evidence of adverse selection.

Our results show that, on average, the transactions costs amount to 61% of the incurred medical expenses compared to the average out-of-pocket co-payment of only about 37%. We also found a counterfactual evidence of moral hazard. If one takes away the insurance from people with coverage, they would decrease their health care consumption by 24 HRK (8%). If you give the insurance to people without coverage, they would increase their health consumption by 16 HRK (8%). The presence of adverse selection was investigated by comparing the empirical distributions of the estimated latent health status across groups of patients with different insurance types relying on the Kolmogorov-Smirnov test. The results indicate the evidence of adverse selection in the sense that patients without the insurance are relatively healthier than patients who bought the coverage.

Institutional framework and data description

The main part of the data for this paper comes from Liu et al. (2012). The original data set consists of all invoices for all outpatient services from a regional hospital in Croatia during the period from March 1 to June 30, 2009. The health care system in Croatia is dominated by a single public health insurance fund: the Croatian Institute for Health Insurance (HZZO). The HZZO offers two types of insurance: the compulsory insurance and the supplemental insurance. The compulsory insurance's coverage is universal and it is funded by a 15% payroll tax whereas the supplemental insurance can be either bought or is extended automatically free of charge to certain categories of citizens. The Croatian public health care system as provided by the HZZO is very similar to the Medicare system in the U.S. The main difference is that the Croatian compulsory insurance insures all citizens whereas Medicare provides limited public health insurance for the 65 years and older citizens. The individuals covered by Medicare can choose to purchase Medigap to cover the gaps in Medicare such as co-pays, deductibles and uncovered expenses (e.g. prescription drugs, prolonged hospital stays, etc.). Medigap in the U.S. system plays the same role as the supplemental insurance for Croatian citizens (for details see Liu et al. 2012).

The full coverage services afforded by the compulsory insurance include: full health care for children under the age of 18, health care of women related to pregnancy and child birth, preventive and curative health care related to infectious diseases, mandatory vaccinations and immunizations, hospital care for all chronic psychiatric patients, complete treatment of all cancers, dialysis, organ transplants, emergency room interventions, house-calls and at-home treatment of patients and prescription drugs from the HZZO basic list. All other health services are subject to a system of co-payments (co-insurance).[1] The insured are required to pay a fraction of the full price of medical care, for example: laboratory, radiological and other diagnostics at the primary health care level (15.00 HRK), specialists' visits and all out-patient services except physical therapy and rehabilitation (25.00 HRK), specialists' diagnostics not at the primary care level (50 HRK), orthopedic and prosthetic devices (50 HRK), out-patient and at-home physical therapy and rehabilitation (25 HRK per day), in-patient care (100 HRK per day), primary care including family physician, gynecologist and dentist (15 HRK), etc. The largest out-of-pocket cost-share amount that a person can pay amounts to 3000.00 HRK per one invoice.[2]

Supplemental insurance is a voluntary insurance that can be acquired by a person 18 years of age or older, having compulsory insurance, by signing a contract with HZZO. A person having the supplemental insurance policy is entitled to full waiver of all medical expense co-payments listed above. The premiums for supplemental insurance are determined as follows: 50.00 HRK per month for an inactive (pensioners, living on social welfare or unemployed) person with the monthly income of less than 5108.00 HRK; 80.00 HRK per month for an inactive person with income higher than 5108.00 HRK; 80.00 HRK per month for an active (employed, self-employed or farmers) person with a monthly net income less than 5108.00 HRK; 130.00 HRK per month for an active person with net income in excess of 5108.00 HRK; 80.00 HRK per month for all family members and dependents.

An interesting feature of the supplemental insurance program is that certain categories of people are exempt from paying the supplemental insurance; in other words, they are entitled to it automatically for free. The list of exemptions is quite long. The top five largest categories are poor people (59.17%), single pensioners (14.11%), people with 80% physical disability (10.86%), blood donors (3.48%) and war veterans (2.96%). Therefore, with respect to the supplemental insurance coverage we distinguish three categories of patients: those that bought the insurance (*Bought* group), those that received the exact same insurance for free (*Free* group) and those that do not have the insurance (*No* group). The analysis in the rest of the paper involves only the comparison of health care consumption for diagnoses subject to the system of co-payments, i.e. all other diagnoses covered in full by the universal compulsory insurance program are ignored. Hence when we refer to patients with no insurance, we mean patients with no supplemental insurance, i.e. those that are only covered by the universal (compulsory) program.

The original data set consists of 105,646 observations. Each observation reflects the invoice for one hospital visit. For the purpose of this estimation, patients who visited the hospital only because of the illnesses that are fully covered by the compulsory insurance are excluded. Next, we delete patients that are younger than 18 because there is no variation in the type of insurance coverage for this group of people, i.e. they are all entitled to supplemental insurance for free. These two cleaning procedures reduced the data set to 70,851 invoices belonging to 22,903 patients. Finally, we also drop observations whose medical costs are beyond 95 percentile in the right tail of the expenditure distribution. The working data set now consists of 58,737 invoices and 21,758 patients and contains the following list of variables: a numeric code for

[1] It appears that the Croatian system does not precisely distinguish co-payments from co-insurance in the sense of the first being the flat fee and the second being the percentage of the cost. The term actually used in English translation means "participation." However, the distinction is immaterial because prices of medical services (payments that providers receive from the HZZO) are fixed by HZZO and do not vary by provider and are also fixed for the period covered by our data.

[2] Listed co-payments were valid for 2009. The exchange rate for the local currency, Croatian Kuna (HRK), as of June 20, 2009 was 1 USD = 5.19 HRK.

Table 1 Summary statistics by insurance category

Variable	Mean	SD	Patients (#)
No group			
Cost per patient (HRK)	257.11	5.28	2451
Co-payment per patient (HRK)	77.42	69.81	2451
Visits per patient	1.94	0.04	2451
Age	40.51	0.29	2451
Male (%)	0.52	0.01	2451
Free group			
Cost per patient (HRK)	338.11	3.78	7512
Co-payment per patient (HRK)	0	0	7512
Visits per patient	2.68	0.03	7512
Age	54.74	0.20	7512
Male (%)	0.41	0.01	7512
Bought group			
Cost per patient (HRK)	350.69	3.04	11,795
Co-payment per patient (HRK)	0	0	11,795
Visits per patient	2.86	0.02	11,795
Age	53.63	0.15	11,795
Male (%)	0.41	0.01	11,795

the type of hospital service provided, compulsory health insurance number, supplemental insurance number (if the patient has one), period covered by the supplemental insurance, numeric code for categories entitled to supplemental insurance free of charge, eligibility category for compulsory insurance (k_1–employed, k_2–farmers, k_3–pensioners, k_4–unemployed, k_5–living on social welfare, k_6–self-employed and other), cost of hospital service, part of the cost covered by compulsory insurance, part of cost covered by supplemental insurance, part of cost covered by participation (co-payment), date of birth and sex of the patient.

We measure health care utilization using total cost per patient during the four-month period covered by the data. The summary statistics of the working data set is displayed in Table 1. The *No* group has smaller cost, younger population and larger percentage of men relative to the *Bought* and the *Free* group. Each patient without the supplemental insurance (*No* group) paid on average 77.4 HRK in out-of-pocket co-payments during the 4-month period which amounts to less than 1% of their income during the same time period. For patients in the other two groups, the co-payment is zero because they are fully covered by the supplemental insurance.

In addition to invoice data set, we also use the Croatian Household Budget Survey (CHBS) for 2009. The CHBS data set is used for the purpose of forecasting the income variable for patients in the invoices data set. The dataset contains information on individual's age, gender, eligibility category for compulsory insurance, supplemental insurance status, household income, income per capita (household income divided by the number of household members), individual income by source (employment, self-employment, unemployment benefits, pensions) and county of residence. The income variable used is defined as the larger amount between the household income per capita and the sum of individual income from all sources. There are a total of 8269 individuals in the CHBS data set; 1430 of them are under the age of

Table 2 Summary statistics: CHBS data for county where hospital is located

Category	Variable	Mean	Median	Min	Max	Obs.
Active	Income	40,081.64	33,333	7533	120,000	
	Age	40.99	42	18	83	168
	Male	0.53	1	0	1	
Inactive	Income	28,493.68	26,243	2425	101,000	
	Age	61.99	67	19	90	137
	Male	0.39	0	0	1	

Inactive group consists of pensioners, unemployed and people living on social welfare. Active group consists of employed and self-employed people and farmers

18 and have been dropped. Among the remaining 6839 observations, 305 are the residents of the county which coincides with the region from which our hospital draws its patients.[3] We break down the 305 observations into active and inactive group based on their eligibility category for compulsory insurance: the active group includes employed, self-employed and farmers; the inactive group includes pensioners, unemployed and living on social welfare. The summary statistics is displayed in Table 2. On average active people in the county earn 11,588 HRK (US$ 1400) annually more than the inactive people.

The model

The model relies on the assumption of a rational economic agent who maximizes his utility function by choosing his optimal health care services m and consumption of composite commodity c subject to a budget constraint. The utility function is additive in aggregate consumption and health care, each in the constant relative risk aversion (CRRA) functional form:

$$U(c_i, m_i; \theta_i, \gamma) = (1-\theta_i)\frac{c_i^{1-\gamma_1}}{1-\gamma_1} + \theta_i \frac{m_i^{1-\gamma_2}}{1-\gamma_2} \tag{1}$$

where γ_1 and γ_2 are risk-aversion coefficients for aggregate and health care consumption. The larger the coefficients, the more risk averse the person with respect to variation in two types of consumption. The utility also depends on latent health status parameter $\theta \in [0, 1]$, which is known to the agent but unobservable by the insurance company. It can be interpreted as the importance weight an agent places on health care and aggregate consumption. In case of bad health, θ is close to one, and the agent would gain relatively more utility from health care consumption and less utility from other consumption.

A consumer's budget constraint requires that his expenditure on aggregate consumption and health care must not be greater than his income minus the insurance premium:

$$c_i + m_i\beta_{ij} \leq y_i - p_j, \tag{2}$$

where y is income, j denotes insurance status (no, bought, free), p_j is the insurance premium and β_{ij} is the co-payment rate which has two parts:

$$\beta_{ij} = \alpha_{ij} + \epsilon_i. \tag{3}$$

[3] The actual name of the county is suppressed for confidentiality reason because revealing the name of the county would automatically reveal the name of the hospital.

In Eq. (3), α_{ij} denotes the percentage of the cost that patients have to pay out of pocket and it depends on the insurance coverage. If the patient has no supplemental insurance, $\alpha_{ij} \in (0, 1)$; if the patient has the supplemental insurance either by buying it or being entitled to it for free, $\alpha_{ij} = 0$. Idiosyncratic cost $\epsilon_i > 0$ represents the non-insurable transactions costs measured as a percentage of the cost of hospital services. It does not depend on the patient's insurance status but varies with agent's income. In particular,

$$\epsilon_i = \frac{t}{T}\frac{1}{\bar{p}}y_i, \tag{4}$$

where t is a parameter to be estimated measuring the required amount of time per visit, $T = 2000$ is the total number of working hours per year (the equivalent of a full-time employment), $\bar{p}$ is the average price per hospital visit, y_i is patient i's annual income and $\frac{t}{T}y_i$ is the lost income per hospital visit.[4] Therefore, the transactions costs associated with hospital visits are measured in terms of lost income. Because $\frac{1}{\bar{p}}$ is the number of hospital visits when the medical expenditure incurred is \$1, ϵ_i is the lost income when the incurred medical expenditure is \$1 and represents the uninsurable transaction costs as a percentage of incurred medical expenditure m_i. The idea behind this specification of the cost factor β_{ij} is the fact that in addition to actual medical expenses which may or may not be covered by the insurance, in order to see a doctor, the patient needs to invest time and other resources, which is costly. These uninsurable costs could be directly related to the lost income due to absenteeism from gainful employment as well as a variety of other things such as the cost of using own vehicle, a bus ticket, a taxi ride, a cost of hiring a baby-sitter or an escort, etc. Notice that without ϵ_i, for patients with supplemental insurance, β_{ij} would be zero and the model would predict the consumption of infinite amount of health care.

The first order conditions for the maximization of utility (1) subject to budget constraint (2) are as follows:

$$\frac{\partial \mathcal{L}}{\partial c_i} = (1-\theta_i)c_i^{-\gamma_1} - \lambda = 0,$$
$$\frac{\partial \mathcal{L}}{\partial m_i} = \theta_i m_i^{-\gamma_2} - \lambda\beta_{ij} = 0,$$
$$\frac{\partial \mathcal{L}}{\partial \lambda} = y_i - P_j - c_i - m_i\beta_{ij} = 0.$$

The standard optimization result shows that the marginal rate of substitution between aggregate consumption and health care consumption equals to the ratio of prices. However, the price of health care that a consumer faces is only the co-payment portion α_{ij} of the actual price plus the transactions costs related to the hospital visit ϵ_i.[5] As a result, the relative price of medical services to aggregate consumption is equal to β_{ij} and the MRS becomes:

$$MRS = \frac{\theta_i}{(1-\theta_i)}\frac{c_i^{\gamma_1}}{m_i^{\gamma_2}} = \alpha_{ij} + \epsilon_i = \beta_{ij} \tag{5}$$

[4] We assume the required amount of time per visit is the same for all patients. This assumption is reasonable because the region from which the hospital draws its patients is rather small so the travel time to reach the hospital should not vary a lot across patients. Secondly, unlike for big hospitals in large cities, the facilities utilization of regional hospitals in Croatia is low, so the waiting time is likely to be equally short regardless of the required procedure.

[5] Here, it is important to realize that even without the supplemental insurance, the patient will almost never pay the full cost of the medical service, because some portion of it is always paid by the universal (compulsory) insurance.

Since a patient only needs to pay $\alpha_{ij} < 1$ portion of the actual health care cost, the price ratio between health care and aggregate consumption is biased towards favoring health care and against general consumption. This "excess" of health care consumption is a standard measure of moral hazard associated with insurance. However, the presence of ϵ_i in (5) changes the calculation because it makes the health care consumption less attractive, thereby potentially mitigating the moral hazard effect. For some non-serious illness it could actually make a difference between seeing and not seeing a doctor.

Since the utility function is strictly increasing, the budget constraint binds at the optimal bundle. Therefore c_i is determined by the equation $c_i = y_i - p_j - m_i\beta_{ij} = y_i - p_j - m_i(\alpha_{ij} + \epsilon_i)$, which substituted into (5) gives:

$$\frac{\theta_i}{(1-\theta_i)} \frac{(y_i - p_j - m_i(\alpha_{ij} + \epsilon_i))^{\gamma_1}}{m_i^{\gamma_2}} = \alpha_{ij} + \epsilon_i. \tag{6}$$

From (6), we could derive an expression for health shock parameter θ_i, which is then used to estimate the risk parameters γ_1, γ_2 and the opportunity cost of time parameter t in ϵ_i from the observable variables:

$$\theta_i = \frac{(\alpha_{ij} + \epsilon_i)m_i^{\gamma_2}}{(y_i - p_j - m_i(\alpha_{ij} + \epsilon_i))^{\gamma_1} + (\alpha_{ij} + \epsilon_i)m_i^{\gamma_2}}. \tag{7}$$

Equation (7) is used to estimate the distribution of θ for groups of patients with various insurance coverages. One could expect that the population who bought the supplemental insurance have different θ distribution than population with no insurance. If the test statistics support that the two θ distributions are drawn from different populations, this will constitute the empirical evidence of selection.

Estimation

The estimation of (7) requires individuals' income which is not available from the invoices data and hence needs to be forecasted. With the imputed income variable, insurance premia and other observed variables, we could estimate the risk parameters γ_1, γ_2 and the time parameter t using a generalized method of moments (GMM) estimator. With these estimated model parameters, we can recover the distribution of θ from (7), which will then subsequently be used to quantify the moral hazard effects and test for the presence of adverse selection.

Income prediction

The income variable for all individuals in the invoices data set is forecasted using the CHBS data. We used the cell average method to predict income. We focus on the 305 observations in the CHBS data, which represent people residing in the county where this regional hospital is located. In the first step, we divide these observations into cells by gender, insurance eligibility category and age. The break down by age was different for each eligibility category to ensure there are enough observations for each group. Then we calculate the average income for people in each cell. The detailed segmentation by gender, age and eligibility category for the CHBS data and the average income for each segment are displayed in Table 3.

In the second step, we use the cell average as the predicted income for people in invoices data set that belong to the same cell. The summary statistics of the predicted income for the people in the invoices data and people in CHBS data are displayed in Table 4 where we

Table 3 Summary statistics: CHBS hospital's county average income by segmentation

Category	Age group	Female	Male
Employed	18–27	34,779	44,480
	28–37	36,433	53,355
	38–46	42,699	59,171
	47–54	63,772	51,390
	55+	46,425	62,767
Farmers	18–27	21,787	15,908
	28–37	16,667	25,009
	38–46	23,298	19,279
	47–54	29,799	24,520
	55+	19,542	19,662
Pensioners	18–54	27,254	39,309
	55–64	27,918	27,359
	65–74	28,598	36,317
	75+	27,461	20,818
Unemployed	18–54	28,645	23,472
	55+	19,375	24,971
Social welfare	18–54	22,353	22,353
	55+	15,885	15,628
Self employed	18–54	26,513	40,623
	55+	27,550	27,550

Average income was calculated for each cell. The age group was different for each eligibility category to ensure enough observations for each cell

Table 4 Summary statistics of the income variable

Sample	Mean	Min	25th	Median	75th	Max	Obs.
Total							
CHBS data	34,877	2425	19,910	29,980	44,132	120,000	305
Invoices data	36,026	15,628	27,461	28,645	42,699	63,772	21,758
Active							
CHBS data	40,081	7533	24,350	33,333	52,362	120,000	168
Invoices data	45,467	15,908	36,433	44,480	59,171	63,772	9865
Inactive							
CHBS data	28,494	2425	17,050	26,243	34,207	101,000	137
Invoices data	28,195	15,628	27,254	27,918	28,645	39,309	11,893

compare the distributions of the predicted income for patients in the invoices data with that of the individuals in the CHBS data. We also compare the income distributions in active and inactive groups. We see that the prediction model works reasonably well, at least as far as pinning down the mean, the median and the 75th percentile.

Based on the imputed income data, we can also predict the monthly premia paid by the two patient groups. As seen from Table 5, for the Active group, one fifth of the sample are required to pay 130 HRK per month in supplemental insurance premium because they earn

Table 5 Predicted insurance premia for patients in the invoices data set

Category	Premium	Count	Percentage
Active	130	1853	8.52
	80	8012	36.82
Inactive	80	0	0
	50	11,893	54.66

monthly income greater than 5108 HRK; the rest of the group pays 80 HRK because they earn less than 5108 HRK per month. In the Inactive group, since the whole sample is predicted to have monthly income of less than 5108 HRK, they are required to pay 50 HRK per month in the supplemental insurance premium.

Model identification

In order to identify the unknown parameters γ_1, γ_2, t, we randomly divide the data set into two groups, i.e, each observation is randomly assigned to one of the two groups. Therefore, the θ distribution for the two groups should be the same. Relying on the fact that the moments for the θ variable in the two subsamples are the same, we use GMM estimation technique to estimate the model parameters. The identification strategy follows Greene (2002, p. 542) who discusses three requirements for identification of the GMM estimator. First, the order condition says the number of moment conditions has to be larger than or equal to the number of parameters. Because we need to estimate three parameters we use four moment conditions. Second, the rank condition says the gradient matrix of the moment conditions must have a row rank that is equal to the number of parameters. Third, there exists a unique vector of parameters that minimizes the objective function. However, as Bajari et al. (2014) point out, in nonlinear parametric models, global identification (second and third identification conditions) is generally difficult to verify, hence these two identification conditions have to be assumed. Intuitively, though, individual variations in latent health status and in income and co-pay rate in the data lead to variations in medical expenditure and general consumption. How the variations in medical expenditure and general consumption are related to the variations in latent health status and income and co-pay rate identify the risk aversion parameters as well as the parameter of the transactions cost function. Of course, functional form assumptions for the utility function and the transactions cost function aid the identification.

By setting the first four moments of health status distribution for two groups to be equal, GMM optimal estimators $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{t}$ minimize the sum of all moment conditions.[6] The mean of the health status distribution for each of the two groups can be written as:

$$\mu_{\theta_k}(\gamma, t) = \sum_{i=1}^{N_k} \frac{1}{N_k} \theta_i(\gamma, t), \quad k = 1, 2 \tag{8}$$

where N_k is the number of patients in group k; γ is a vector $[\gamma_1 \ \gamma_2]$. The variance of health status distribution for each of the two groups can be written as:

$$Var_{\theta_k}(\gamma, t) = \sum_{i=1}^{N_k} \frac{1}{N_k} (\theta_i(\gamma, t) - \mu_{\theta_k}(\gamma, t))^2, \quad k = 1, 2. \tag{9}$$

[6] Bajari et al. (2014) used the same approach. However they have 3 years worth of data and they assume that θ distribution does not change from 1 year to the next.

The skewness of health status distribution for each of the two groups can be written as:

$$Sk_{\theta_k}(\gamma,t)=\sum_{i=1}^{N_k}\frac{1}{N_k}\frac{(\theta_i(\gamma,t)-\mu_{\theta_k}(\gamma,t))^3}{var_{\theta_k}(\gamma,t)^{3/2}},\quad k=1,2. \tag{10}$$

and, finally, the kurtosis of health status distribution for each of the two groups can be written as:

$$Ku_{\theta_k}(\gamma,t)=\sum_{i=1}^{N_k}\frac{1}{N_k}\frac{(\theta_i(\gamma,t)-\mu_{\theta_k}(\gamma,t))^4}{var_{\theta_k}(\gamma,t)^{2}}-3,\quad k=1,2. \tag{11}$$

To simplify the notation, we introduce vector $w=(m,y,p_j,\alpha_j)$, and define moment conditions as $h(w,\gamma,t)$. In case of the mean we have one sample moment conditions:

$$h_1(w,\gamma,t)=\mu_{\hat{\theta}_1}(\gamma,t)-\mu_{\hat{\theta}_2}(\gamma,t) \tag{12}$$

The sample moment conditions for variance, skewness, kurtosis are of the similar form. Since two groups are drawn from same population, it follows that $E[h(w,\gamma,t)]=0$. The GMM estimators, $\hat{\gamma}_1,\hat{\gamma}_2,\hat{t}$ minimize the sum of all 4 squared sample moment conditions, which can be written compactly as the following objective function:

$$[\hat{\gamma}_1,\hat{\gamma}_2,\hat{t}]=argmin\sum_{k=1}^{4}h_k^2. \tag{13}$$

We found the minimum of the objective function and hence the estimates $\hat{\gamma}_1,\hat{\gamma}_2,\hat{t}$ by a grid search over the parameter values $\hat{\gamma}_1\in[0,10]$, $\hat{\gamma}_2\in[0,10]$ and $\hat{t}\in[0.5,8]$. The grid increment for γ_1,γ_2 was set at 0.01 and the grid increment for t was set at 0.1. We restrict t to be in the interval between half an hour and 8 h because patients came to the hospital for outpatient services only.

The main support for our identification strategy comes from the law of large numbers. With two random sub-samples from the same parent sample, the moments of the same observable variables should be the same. The means for each observable variable for both sub-samples are presented in Table 6. We also test whether the differences are statistically significant and found that none of the differences are statistically significant which supports our identification assumption.

Estimation results

The estimates of the model parameters and standard errors are displayed in Table 7. The standard errors of the estimates are obtained through bootstrapping. In each iteration of the bootstrapping exercise, we randomly draw observations with replacement from invoice data. We run the grid search with the new sample, a new set of estimates $\hat{\gamma}_1,\hat{\gamma}_2,\hat{t}$ would be found. We repeat this procedure 100 times and the standard deviations of the 100 estimates are taken as the standard errors of the point estimates.

The results show that people are more risk averse when it comes to their health compared to risk aversion associated with aggregate consumption.[7] The estimate of t was found to be $\hat{t}=5$, indicating that, on average, each visit to the hospital will take a patient 5 h. Using $\hat{t}$,

[7] The results are comparable to the results obtained by Bajari et al. (2014) who also found that the risk aversion parameter for health care consumption is larger than that of the general consumption. Their estimates of γ_1 are in the range of [1.88,1.98] and the estimates of γ_2 are in the range of [3.12, 3.27].

Table 6 Test of randomness of sub-samples

Category	Mean 1	Mean 2	Test result	*tstat*	*p* value
Age	52.55	52.53	Fail to reject	0.10	0.92
Male	0.43	0.43	Fail to reject	0.07	0.95
Cost	339.06	332.56	Fail to reject	1.48	0.14
Insurance	2.43	2.43	Fail to reject	0.55	0.58
k1	0.38	0.38	Fail to reject	0.25	0.80
k2	0.05	0.06	Fail to reject	– 1.00	0.32
k3	0.40	0.40	Fail to reject	– 0.65	0.52
k4	0.13	0.12	Fail to reject	1.88	0.06
k5	0.02	0.02	Fail to reject	– 1.03	0.30
k6	0.02	0.02	Fail to reject	– 0.45	0.66

Test result returns a decision for the null hypothesis that the data in two vectors come from independent random samples from normal distributions with equal means and unknown variances

Table 7 Estimates of model parameters

Parameter	Estimate	SE	t-statistic
γ_1	2.26	0.20	11.18***
γ_2	5.99	0.33	18.18***
t	5	0.47	10.62***

Standard errors are calculated based on 100 bootstrap iterations. ***indicates 1 % significance level; **indicates 5 % significance level and *indicates 10 % significance level

we can calculate the uninsurable transactions costs of hospital visits as a percentage of health care cost using (4). On average, it amounts to 61% of the health care cost (with the standard error of 0.22) and is larger than the average co-payment rate for patients in the No group (37%).[8] Therefore, the transactions costs are critical component of the total cost of health care and must not be ignored. In addition, as mentioned above, the model without these costs cannot be estimated at all. This is because the co-pay rate for patients with supplemental insurance is zero and the model predicts an infinite consumption of medical services at zero price. Of course, in real life, even people with *Cadillac* health insurance do not consume infinite quantities of health care, hence such a model would be inconsistent with the observed behavior.

The estimated model parameters also allow us to compute compensated and uncompensated demand elasticities for health care. Implicit differentiation of (6) yields,

$$\frac{dm_i}{d\beta_{ij}} = -\frac{\frac{\theta_i}{(1-\theta_i)} \frac{\gamma_1 (y_i - p_j - m_i \beta_{ij})^{\gamma_1 - 1}}{m_i^{\gamma_2 - 1}} + 1}{\frac{\theta_i}{(1-\theta_i)} \frac{\gamma_1 (y_i - p_j - m_i \beta_{ij})^{\gamma_1 - 1}}{m_i^{\gamma_2}} \beta_{ij} + \frac{\theta_i}{(1-\theta_i)} \frac{\gamma_2 (y_i - p_j - m_i \beta_{ij})^{\gamma_1}}{m_i^{\gamma_2 + 1}}}$$

8 This percentage represents the average of individual co-payment rates, whereas the ratio of two means (co-payment per patient of 77.42 HRK and cost per patient of 257.11 HRK) for the No group in Table 1 is only 30%.

Table 8 Price elasticities of demand for health care

	Mean	SD	Min	Max
η	− 0.1689	0.0018	− 0.1804	−0.1670
η^C	− 0.1675	0.0006	− 0.1699	−0.1668

and the uncompensated (Marshallian) demand elasticity $\eta = \frac{dm_i}{d\beta_{ij}}\frac{\beta_{ij}}{m_i}$ can be easily derived. Also, implicit differentiation of (6) yields

$$\frac{dm_i}{dy_i} = \frac{\frac{\theta_i}{(1-\theta_i)}\frac{\gamma_1(y_i-p_j-m_i\beta_{ij})^{\gamma_1-1}}{m_i^{\gamma_2}}(1-m_i\frac{t}{T}\frac{1}{p}) - \frac{t}{T}\frac{1}{p}}{\frac{\theta_i}{(1-\theta_i)}\frac{\gamma_1(y_i-p_j-m_i\beta_{ij})^{\gamma_1-1}}{m_i^{\gamma_2}}\beta_{ij} + \frac{\theta_i}{(1-\theta_i)}\frac{\gamma_2(y_i-p_j-m_i\beta_{ij})^{\gamma_1}}{m_i^{\gamma_2+1}}}.$$

and by Slutsky decomposition, the compensated (Hicksian) demand elasticity becomes $\eta^C = \frac{dm_i^c}{d\beta_{ij}}\frac{\beta_{ij}}{m_i^c} = \frac{dm_i}{d\beta_{ij}}\frac{\beta_{ij}}{m_i} + \beta_{ij}\frac{dm_i}{dy_i}$.

The results are reported in Table 8. The mean uncompensated elasticity is − 0.1689 and the mean compensated elasticity is − 0.1675. These estimates are similar to the findings in the previous literature. For example, Vera-Hernandez (2003) reported − 0.108 for both uncompensated and compensated elasticities when the co-pay rate is between 0 and 25% and Manning et al. (1987) found uncompensated elasticity of − 0.13.

Using estimated model parameters we can construct the distribution of θ based on (6). In Fig. 1 we provide the histogram plot (empirical pdf) of the distribution for θ. We also regress θ_i on patients' individual characteristics. Results are reported in Table 9 and, as expected, they indicate that older people have worse health and higher income people have better health. The gender difference in health, as indicated by the positive male dummy, is statistically significant, indicating men have worse health.

Asymmetric information effects

The use of moral hazard and adverse selection terms has its origins in the insurance literature and then subsequently spread into contract theory and information economics. The contract theory refers to moral hazard as an asymmetric information problem arising when agent's (insured's) behavior is not observable by the principal (insurance company). In the context of health insurance, however, moral hazard is often used in reference to the price elasticity of demand for health care, conditional on underlying health status (Paully 1968; Cutler and Zeckhauser 2000; Einav et al. 2013). The approach that we use in the treatment of moral hazard is conceptually in line with this mainstream health insurance literature, also referred to as ex-post moral hazard. In other words, our approach does not consider the potential impact of insurance on the underlying health θ. When it comes to adverse selection, both strains of the literature refer to the same problem which appears when the agent (insured) holds private information before the relationship with the principal begins (i.e., before the insurance contract is signed). In this case, the principal can possibly verify the agent's behavior, but the optimal decision or its cost depends on agent's type (for example her health status) of which the agent is the only informed partly.

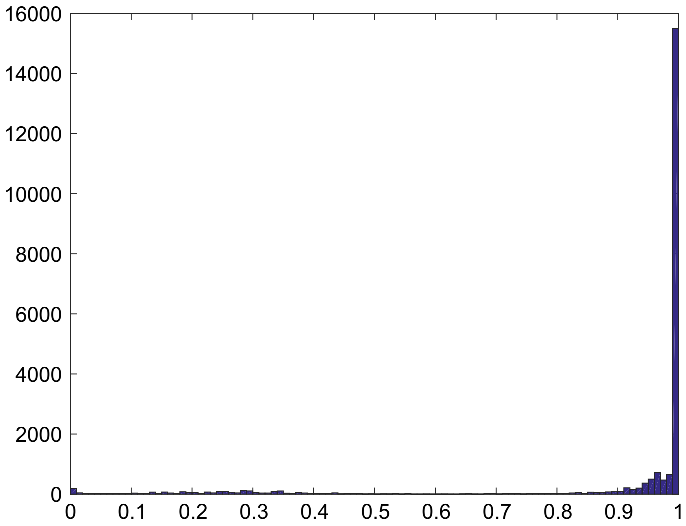

Fig. 1 Empirical pdf of health status θ

Table 9 Regression of health status θ on individual characteristics

Parameter	Estimate	SE	t-statistic
Intercept	1.1693	0.0526	22.25***
Age	0.0013	0.0005	2.42**
Age-square	– 0.00001	0.000005	– 2.42**
Male	0.0097	0.0032	3.03***
Log(income)	– 0.0279	0.0051	– 5.46***

***Indicates 1 % significance level; **indicates 5 % significance level and *indicates 10 % significance level

Moral hazard

To estimate the magnitude of moral hazard, we run two counterfactual experiments. First, we take away the supplemental insurance from people in *Bought* group and calculate their counterfactual health expenses in the absence of supplemental insurance. In the first experiment, a patient has to pay the part of cost that was originally covered by supplemental insurance out of pocket. This means that their out of pocket expenses as a percentage of the health care cost, which was only ϵ_i in the absence of supplemental insurance, increases to $(\alpha_{ij} + \epsilon_i)$. The consumer is also provided with a lump sum income transfer equal to the amount originally covered by supplemental insurance to ensure the original consumption bundle (c_1, m_1) is affordable. This removes the income effect from the price change in health care relative to other goods and allows us to focus on the substitution effect.[9]

[9] The patients in the *Free* group are not used in this experiment because of the data coding problem. In many instances the entire cost of the visit has been charged to the compulsory insurance and zero to the supplemental insurance. Hence, when losing the insurance the patient in the *Free* group is now required to pay certain percentage of the cost as a co-payment, but any percent of zero is still zero. Notice, however, that this data coding problem does not affect the estimation for $\hat{\gamma}_1, \hat{\gamma}_2, \hat{t}$ because for estimation purposes we only need total cost per patient rather than a part covered by compulsory and a part covered by the supplemental insurance.

Next, we need to explain how to calculate m_2 for each individual in *Bought* group. Denote the lump sum income transfer as $T_i = \alpha_{ij} m_{1i}$, where α_{ij} is the portion covered by supplemental insurance (observed in the data). In the counterfactual scenario, patient i pays the amount $\alpha_{ij} m_{2i}$ out of pocket and the budget constraint becomes:

$$c_{2i} + m_{2i}(\alpha_{ij} + \epsilon_i) \leq y_i - p_j + T_i \tag{14}$$

Next, we need to solve the optimization problem. With the binding budget constraint, c_2 can be expressed as $c_{2i} = y_i - p_j - m_{2i}(\alpha_{ij} + \epsilon_i) + T_i$ and the agent's utility function that needs to be maximized becomes:

$$U(m_{2i}, p_j, y_i; \theta_i, \epsilon_i, \gamma) = (1 - \theta_i)\frac{(y_i - p_j - m_{2i}(\alpha_{ij} + \epsilon_i) + T_i)^{1-\gamma_1}}{1 - \gamma_1} + \theta_i \frac{m_{2i}^{1-\gamma_2}}{1 - \gamma_2}. \tag{15}$$

The first order conditions set the marginal rate of substitution between aggregate consumption and health care equal to the price ratio. In the absence of supplemental insurance, a consumer pays his share $(\alpha_{ij} + \epsilon_i)$ out of pocket. The price ratio is then equal to $(\alpha_{ij} + \epsilon_i)$ and the marginal rate of substitution becomes:

$$MRS = \frac{\theta_i}{(1 - \theta_i)} \frac{(y_i - p_j - m_{2i}(\alpha_{ij} + \epsilon_i) + T_i)^{\gamma_1}}{m_{2i}^{\gamma_2}} = \alpha_{ij} + \epsilon_i. \tag{16}$$

Since the health status parameter θ_i, risk parameters γ_1, γ_2, and the idiosyncratic cost ϵ_i are all unchanged, we can use their estimates obtained in "Model identification" section and solve for the only unknown variable, m_{2i} using (16). The difference between the observed health care consumption m_{1i} and the counterfactual health care consumption m_{2i} is caused by the change in price ratio and represents a measure of moral hazard. The standard errors of the estimates for moral hazard are obtained through bootstrapping. We calculate estimate of moral hazard with the updated $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{t}$ in each iteration of the bootstrapped invoice samples. Standard deviations of the 100 estimates are taken as standard errors of the point estimates.

For each patient, the moral hazard is measured by the difference between the counterfactual and the original health care expenditure, $\Delta m_i = m_{2i} - m_{1i}$ or as a percent change in the original health care expenditure, $\%\Delta m_i = \frac{m_{2i} - m_{1i}}{m_{1i}}$. The averages across all patients in different groups are reported in Table 10 . The results show that people in *Bought* group would spend 23.80 HRK or 7.66% less on health care if we take away their supplemental insurance. Because our data is limited only to the observations of people who came to the hospital and sought medical help, the estimates of moral hazard would normally be impacted by the "users only" data problem. However, in this particular counterfactual experiment, the estimate of moral hazard is unbiased because taking away insurance from non-users do not change their behavior. People who did not visit the doctor when they had insurance, surely would not visit the doctor when they don't have insurance.

Using this counterfactual experiment it is also meaningful to sum up all individual measures of moral hazard to come up with the aggregate measure of moral hazard for the county/hospital as a whole. As seen from Table 10, the aggregate 4-months hospital level reduction in health care consumption due to elimination of moral hazard amounts to 280 thousand HRK (about 54 thousand dollars) or 6.79%.

In the second counterfactual scenario we give supplemental insurance to the patients in the *No* group and calculate their counterfactual health expenses assuming they have supplemental insurance. In this scenario the patients only need to pay $\epsilon_i m_i$ out of pocket. There is also an income transfer, $T_i = -\alpha_{ij} m_{1i}$, which is negative because it takes away part of the

Table 10 Counterfactual effects of moral hazard

Group	Insured (Bought)	Uninsured (No)
Mean (Δm_i)	– 23.80 (2.74)	15.73 (2.02)
Mean ($\%\Delta_i$)	– 7.66 (0.86)	7.59 (0.95)
Total reduction (HRK)	– 280,755 (32,305)	–
Percent reduction (%)	6.79 (0.78)	–

$\Delta m = m_2 - m_1$; $\%\Delta m = \frac{m_2 - m_1}{m_1}$; standard errors are in the parentheses, obtained with 100 bootstrapping iterations. Total reduction is the sum of Δm_i. Percent reduction is total reduction divided by total cost. All estimates are significant at 5% level

income which was originally spent on health care consumption. Then, the budget constraint becomes:

$$c_{2i} + m_{2i}\epsilon_i \le y_i - p_j + T_i. \tag{17}$$

Substituting the binding budget constraint for c_{2i} in the utility function yields:

$$U(m_{2i}, p_j, y_i; \theta_i, \epsilon_i, \gamma) = (1-\theta_i)\frac{(y_i - p_j - m_{2i}\epsilon_i + T_i)^{1-\gamma_1}}{1-\gamma_1} + \theta_i \frac{m_{2i}^{1-\gamma_2}}{1-\gamma_2}. \tag{18}$$

Finding maximum would reveal the optimal allocation bundle achieved at the point where the marginal rate of substitution between aggregate consumption and health care equals the price ratio ϵ_i and the marginal rate of substitution will once again become:

$$MRS = \frac{\theta_i}{(1-\theta_i)} \frac{(y_i - p_j - m_{2i}\epsilon_i + T_i)^{\gamma_1}}{m_{2i}^{\gamma_2}} = \epsilon_i. \tag{19}$$

Same as before, for each observation, the only unknown variable is m_{2i} which could be solved for each patient using (19). We expect the counterfactual health care m_{2i} to be greater than the observed m_{1i}. Thus, the difference between the counterfactual m_{2i} and the observed m_{1i} is the amount a patient would over-consume as a result of price distortion due to the supplemental insurance and it represents an alternative measure of moral hazard.

As seen from Table 10, people in the *No* group would have spent 15.73 HRK or 7.6% more on health care once they were provided with the supplemental insurance. This measure of moral hazard suffers from the "users only" data problem because in this counterfactual experiment we cannot give the insurance to people in the *No* group who never showed in the hospital (non-users) because we don't know who they are and how many of them there are. Therefore this measure surely understates the true magnitude of moral hazard in the general population.

Adverse selection

In the presence of adverse selection, the patients with no supplemental insurance (*No*) and the patients who bought the supplemental insurance (*Bought*) should have different health status distributions. We first estimate the relationship between patients' characteristics and insurance status using logistic regression. The outcome variable is the insurance status: for the *Bought* group $Y_i = 1$ and for the *No* group $Y_i = 0$. The results give the marginal effect of the regressors on the probability of purchasing insurance. The first specification includes only demographic covariates: age, gender and income. We expect the marginal effects of age and income to be positive and gender (male) to be negative, meaning that older, richer and female patients are more likely to buy the supplemental insurance relative to their counterparts. The second logit model includes demographic covariates and estimated health status $\hat{\theta}$. A larger value of θ denotes relatively worse underlying health status. We expect that the estimated health status $\hat{\theta}$ has a positive marginal effect because patients who bought the supplemental insurance did so in anticipation of frequently using it.

In addition to logistic regression, the presence of selection can be also tested by comparing estimated θ distributions across different groups. In the presence of adverse selection, we would expect the distributions of the latent health status be significantly different across different groups, with higher θ patients choosing to purchase insurance and lower θ patients choosing not to purchase insurance. The absence of adverse selection would be indicated by the health status distributions being identical across different groups. We perform the Kolmogorov-Smirnov test for the equality of θ distributions across different groups. The null hypothesis is that θ distributions for two groups come from the same population. We also use Kolmogorov-Smirnov test to determine whether the cdf of θ distribution for one group stochastically dominates that of the other. The group with a dominating cdf has more consumers with lower value of θ (healthier). One would expect that in the presence of adverse selection, the patients in the No group should be comparatively healthier (lower value of θ) and the cdf of θ distribution in the No group should stochastically dominate that of the $Bought$ group.

Finally, one cannot rule out the presence of favorable selection either. This is because people can buy more or less insurance for reasons which are not only related to their risk-aversion and health status but could be additionally impacted by other sources of unobserved heterogeneity.[10] In the presence of favorable selection, the cdf of θ distribution of the $Bought$ group should stochastically dominate that of the No group.

The results for logistic regression are displayed in Table 11. Most results in Model 1 are as expected. The marginal effect of age is positive and the marginal effect of gender (male) is negative. It means that older and female patients are more likely to purchase the supplemental insurance than their counterparts. An unexpected result is that income has negative marginal effect which means that richer individuals are less likely to buy the supplemental insurance than the poor ones. This result can be interpreted by realizing that rich people can self-insure themselves against adverse effects of illness. This is especially true in Croatia where the compulsory insurance provides a very generous safety net for all citizens whereas the supplemental insurance covers expenses which are unlikely to cause a serious financial hardship for more affluent citizens. The results in Model 2 which includes the estimated latent health status do not reverse any of the results from Model 1. As far as the health status is considered, it has positive effect on $Bought$ group. With larger value of θ indicating worse health, this result suggests that people without insurance tend to be relatively healthier and people who decided to buy the insurance tend to be in worse health.

Next, we test the adverse selection effect by comparing θ distributions. The two-sided and one-sided test results are reported in Table 12. The two-sided test results show that patients in the two groups have different health status distributions and the results are statistically significant at 1%. Finally, we test whether the cdf of the θ distribution for No group dominates that of $Bought$ group. The group with the dominating cdf of the θ distribution has more people on the lower end of the distribution, which means it has larger percentage of healthier people. The null hypotheses that the distributions are the same are tested against the alternative

10 Fang et al. (2008) found evidence of advantageous selection in the Medigap insurance market and suggested that the sources of this advantageous selection include the insureds' income, education, longevity expectations, financial planning horizons and especially the cognitive ability.

Table 11 Testing for adverse selection: logistic regression of insurance choices

Group	Variable	Model 1	Model 2
Bought	Gender (Male = 1)	− 0.0450*** (0.0061)	− 0.0456*** (0.0061)
	Age	0.0061*** (0.0002)	0.0061*** (0.0002)
	Log(income)	− 0.0789*** (0.0092)	− 0.0775*** (0.0092)
	$\hat{\theta}$		0.0388*** (0.0126)

Marginal effects are presented. Standard errors are in parentheses

Table 12 Tests of adverse selection: K-S statistics for equality of θ distribution

Group (*No* and *Bought*)	Statistics	*P* value	Results
Two-sided	0.128	0.000	Reject
One-sided	0.128	0.000	Reject

that the cdf of the θ distribution for *No* group dominates that of the *Bought* group. The one-sided test results show that the cdf of the θ distribution for the *No* group significantly dominates that of the *Bought* group. It means healthier people self-selected themselves into the *No* group, while people with comparatively worse health self-selected themselves into the *Bought* group. These results provide strong, statistically significant, evidence of adverse selection.

The enlarged versions of cdf distributions of θ for the two groups are plotted in Fig. 2. The graph clearly shows that the cdf of θ distribution for the *Bought* group is stochastically dominated by that of the *No* group, indicating that people in the *No* group are generally healthier than people in the *Bought* group.

Conclusion

This paper uses a structural approach to estimate clean moral hazard effect in health insurance, net of possible influences of adverse selection. We found positive and economically meaningful effect of moral hazard and also a statistically significant effect of adverse selection in the population of hospital patients.

An important methodological contribution of our paper is to take into account the individual patients' in-insurable transactions costs associated with medical care consumption. To the best of our knowledge this is the first attempt in the literature to incorporate such cost into a structural estimation of health care demand. We argue that this cost does not depend on the providers' price nor the insurance type but depends on agent's income. The idea behind this specification is the fact that in addition to actual medical expenses which may or may not be covered by the insurance, different people could have different transaction costs associated with visiting a hospital or a doctor, which for certain minor illnesses could deter the health care consumption thus mitigating the moral hazard problem.

The generalization of the obtained results for the purposes of country level and international comparisons is somewhat hampered by the fact that hospital invoices data is comprised of users only, i.e., we don't have data for insured and uninsured citizens with zero medical consumption in the given period. As it turns out, the obtained structural model parameter estimates $(\hat{\gamma}_1, \hat{\gamma}_2, \hat{t})$ are still consistent because the structural model is assumed for users

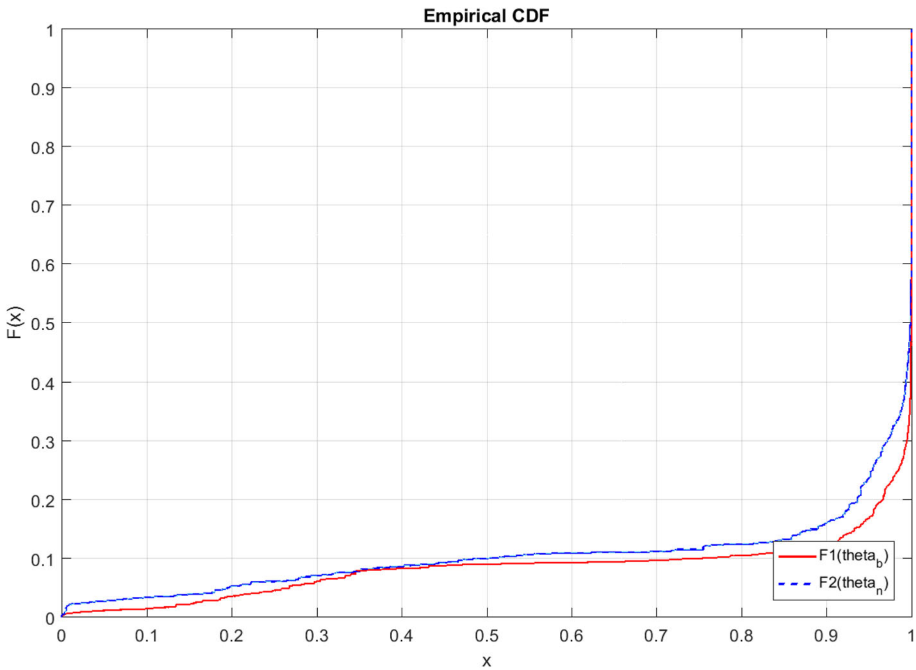

Fig. 2 Empirical CDF of θ for two groups (Enlarged)

and non-users alike and Eq. (7) used to estimate θ_i for individuals with different insurance coverage is also valid for both users and nonusers. However, two important consequences of the *users only* data still remain.

First, the two counterfactual moral hazard scenarios are markedly different. The scenario where we take away the supplemental insurance from the insured users and simulate their counterfactual health expenses in the absence of this insurance gives the correct estimate of the moral hazard effect at the aggregate (hospital) level. This is true in light of the fact that the insured nonusers are not going to be impacted by taking away the insurance from them because if they did not go to the hospital when they had insurance, they surely will not go when they don't have the insurance. The second scenario where we give the insurance to uninsured users suffers from the fact that uninsured users group does not encompass people who did not seek medical attention precisely because they lacked the insurance. Therefore, giving the insurance to uninsured citizens would impact not only users but potentially also nonusers who do not appear in our data. Hence the second scenario is surely going to under-estimate the magnitude of the moral hazard. The difference between two scenarios is attributable to the *users only* data problem.

Second, the tests for adverse selection are also impacted by the *users only* data problem because these tests should be based on the distribution of the unobserved health status θ for the entire population whereas ours are based on users only. Our estimates of θ_i overstate the true health status in the overall population, making it worse than it really is. There are two reasons for this phenomenon, both pooling in the same direction. First, among those insured, it is reasonable to assume that most of those that need medical help will actually demand it and hence will show up as users. Only those, with relatively minor illnesses and high transactions costs associated with hospital visits will not seek medical attention when they need it and will not show up as users. The rest of the insured population simply did not need medical attention and never showed up in the hospital. Hence, the actual health status of the entire *Bought* group is likely to be better (lower θ) than the actual patients (users only) based estimates. Next, the users only based estimates of θ_i for the *No* group is also likely to overstate the true health status of this entire group because it is possible that some people who do not have the insurance did not show up in the hospital to seek medical attention precisely because they did not have the insurance. The unobserved health status of those individuals (nonusers) is likely to be better than those uninsured individuals who actually sought medical attention since their condition was too serious to forgo the treatment. Whether performing the adverse selection tests based on the distributions of unobserved health status reflective of the entire population would change the previously obtained results is impossible to predict.

Compliance with ethical standards

Conflict of interest No potential conflicts of interest exist.

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