

Health care utilization of older people in Europe - Does financing structure matter?

Anikó Bíró*

Central European University

December 10, 2009

Abstract

The effect of public financing on health care utilization is analyzed based on various empirical specifications. Inpatient care, and utilization of outpatient care provided by general practitioners and specialists are considered. Two-stage utilization decisions, and the endogeneity of private health insurance are taken into account in the empirical models.

The empirical findings indicate positive effect of public financing on health care utilization, which is modest in absolute terms but not negligible in relative terms. There is no clear evidence for an increasing effect of supplementary private health insurance on utilization.

The results are based on the first wave of the Survey of Health, Ageing and Retirement in Europe, a cross-national micro database of individuals aged 50 or over.

1 Motivation

Public financing of health care and private health insurance coverage can influence the demand for medical care, basically through their effect on observed health care prices. In addition, public spending on health influences the demand for supplementary private health insurance. Taking into account this effect, how does public health spending influence utilization of health services by people aged 50 and above? In this paper I show that for the analyzed ten European countries the differences in health care usage due to different reliance on public financing are generally modest in magnitude. In the Survey of Health, Ageing and Retirement in Europe (SHARE) data there is cross-country variation in the generosity of public health system, and there are observations on a wide range of individual characteristics. These data properties make the identification of health care financing effects possible. As an empirical novelty, in the preferred specification a sample selection model for count data is estimated, where a binary regressor (private health insurance coverage) is endogenous both in the selection and main equation.

The financing of health care is a critical issue in health policy. Avoiding the expansion of government expenditures on health might be supported by higher reliance on private health insurance. On the other hand, a health insurance system based on private insurance might violate the universal access to basic health care services. This paper contributes to the issue whether financing structure matters for health care utilization. If higher share of public financing or private health insurance coverage implies more utilization

*E-mail: cphbia01@ceu-budapest.edu

of health care services *ceteris paribus*, then it can indicate two types of problems. First, it might show over-utilization among the insured individuals, second, it can reveal under-utilization among the uninsured ones. Both problems imply welfare losses, considering the costs and benefits of health care.

Based on the row data, relatively big differences can be observed in the reported numbers of nonzero doctoral visits and hospital nights across countries, whereas the differences in the share of respondents reporting any utilization are more moderate. In addition, within the category of outpatient care I separately analyze the utilization of general practitioner and specialist care. Opposite to the visits to general practitioners, the ratio of respondents reporting specialist care utilization varies considerably across countries, but the variation in the number of visits is relatively small. As I show in this paper, the effects of individual- and country-specific factors on the utilization of overall doctoral care and specialist care are different.

The cross-country variations in health care utilization can be explained by several factors, like different needs for health care, attitudes towards medical services, price of health care, and the health insurance system might also play a determinant role. In this paper my aim is to analyze in details the partial effect of public health financing on health care utilization. This is an important issue for health policy because of several reasons: higher health care utilization might improve health status, and health increases individual lifetime utility. On the other hand, generous public health system can induce over-utilization in health care, thus leading to aggregate welfare losses. Furthermore, health care utilization has financial consequences both for the individual and for the public budget. Focusing only on individuals aged 50 or over limits the overall relevance of the empirical results, but with the population ageing in Europe this age group tends to represent an increasing share of the population. Moreover, since health problems are generally more prevalent among older individuals, the health care demand of people 50+ is of high importance for health policy issues.

I provide a detailed empirical analysis of the determinants of medical services used, focusing on the effects of health financing. After discussing the research framework (section 2) and the basic features of health care financing structures in the analyzed countries (section 3), I present the data used in the empirical analysis (section 4). The next step (section 5) is to build up and estimate the empirical models, using different modelling assumptions. Finally I simulate the influencing effects of public health expenditures and supplementary private health insurance coverage based on the empirical models, in order to interpret and compare the results of the nonlinear models (section 6).

2 Related literature and framework of analysis

The demand for voluntary private health insurance, and its effect on medical expenditures based on the SHARE data are analyzed to some extent by Holly et al. (2005), and Paccagnella et al. (2008). A novelty in my research is to analyze the complex relationships between public health expenditure, supplementary private health insurance, and medical services based on this new database. In addition, I compare the implications of four different modelling strategies. The analysis framework is related to, but simpler than the papers of Davis (2006) and De Nardi et al. (2006). These papers provide a theoretical background to health care demand, but I do not model here savings decisions and I do not estimate a structural model of utility maximization. The applied version of the database (wave1 data) is more appropriate for a reduced form analysis. Similar modelling tools, cross-country comparisons in Europe are applied, but different research question (relationships between health and socioeconomic status) is analyzed by Cavaco et al. (2007). A review of papers with similar research questions is provided by Hadley (2003). Based on the SHARE database Maurer (2006) also makes some comparisons of health care utilization in European countries, focusing on

the responsiveness to health care needs, and on the effect of individual socioeconomic backgrounds. In a recent paper Bolin et al. (2009) compare the importance of individual and institutional factors in outpatient care utilization in Europe (using SHARE data), and find greater role of individual factors. My analysis differs from that of Bolin et al. (2009) not only in the empirical specification and investigation of inpatient care as well, but also in focusing on the effects of health insurance and health care finance indicators. Bago d’Uva - Jones (2009) use the European Community Household Panel (ECHP) to analyze the determinants of outpatient care utilization in Europe - they focus on the effect of income. They find cross-country differences, but generally find that richer individuals utilize specialist care to a higher extent than poorer individuals.

There are few results about the effect of public health expenditures on health care demand in Europe. As for the U.S., the general finding in the related literature is that health insurance coverage (or higher co-insurance rate) increases the demand for health services, due to the reduced costs of utilization. Such result is found among others by Manning et al. (1987) - based on the RAND Health Insurance Experiment, and by Gibbons - Wilcox-Gok (1998) - based on the National Medical Expenditure Survey. A different strand of the literature uses aggregate data to analyze the determinants of health care utilization and aggregate health expenditures. These studies typically use OECD data. As summarized by Gerdtham - Jonsson (2000), there is a consensus in the literature that aggregate income is a crucial factor in explaining health expenditure differences across the countries, and it has positive effect. This relationship is found e.g. by Hitiris - Posnett (1992), who at the same time do not find any significant effect of the public health expenditure share within total on per capita health expenditures. In contrast, Gerdtham et al. (1992) estimate a significantly negative effect of public financing share on health expenditures, but they also find a positive effect of per capita GDP.

The path diagram for my analysis is presented in Figure 1. The final outcomes of interest are the number of doctor visits and of hospital nights. The box colored grey shows outcome variables which are out of the scope of this paper: the effect of health care utilization on health outcomes and on survival probability are not analyzed here. A basic assumption is no reverse causality from the outcome variables to health care financing structure and private health insurance (PHI) coverage, thus PHI status is predetermined. It is also assumed that the public health expenditure indicator, and the indicators of health care resources are exogenous - assuming that the marginal effects of individual decisions are negligible.

A key assumption throughout this paper is that PHI coverage is predetermined. The main reason for this assumption is that individuals with pre-existing conditions, and above a given age are generally excluded from contracting PHI (details can be found in Mossialos - Thomson (2004)). For people aged above 50, the decision about buying private health insurance is likely to be made during the earlier working life.¹ This decision can be influenced by the insurance costs and availability, and by the potential benefits of such a contract, which depends on risk-aversion, risk of future health problems and potential health care expenditures (influenced also by the health care system). Although PHI is pre-determined in this model, some of the influencing factors of coverage are time-invariant, like gender, education, cohort-effects, or also the main features of the health care system, at least in the short to middle run. Thus, it is possible to estimate the effect of such time-invariant variables on the likelihood of PHI coverage. An additional difficulty in identifying the determinants of PHI coverage is that in some countries the majority of health insurance policies are purchased by groups, rather than by individuals. These groups are typically employment-based groups, which have a predominant

¹The question about PHI coverage is not included in the SHARE Wave2 data, but there is a question about change in health insurance since the last interview. Although this question is not restricted to private insurance, 89% of the respondents report no change in coverage.

role e.g. in the Netherlands and in Sweden (according to Mossialos - Thomson (2004), Table 10).

My model has two main parts:

1. Decision on supplementary private health insurance coverage;
2. Utilization of medical services.

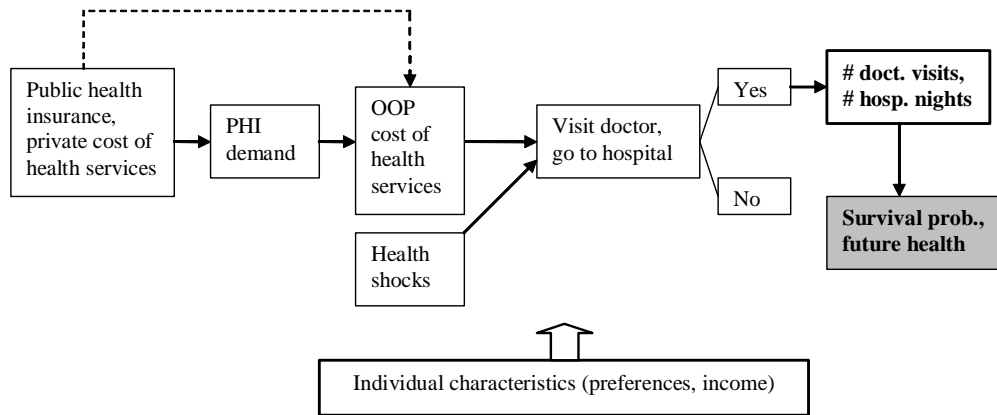


Figure 1: Modelling framework

How can these decisions be put into a utility maximization framework, assuming rational agents? For example, Davis (2006) and Han (2006) build up complex models that include utilization of and expenditures on health care. My aim here is not to estimate the parameters of a structural model, but to provide some theoretical motivation to the empirical analysis. A detailed underlying model for two periods is described in Appendix A. The key point is that more generous public health care and PHI can decrease the realized price of health care services, which increases demand.

Individuals maximize their expected future lifetime utility, which depends on consumption and health. Future health and survival probability are influenced by utilization of health care. Decision about making an initial contact with a physician or going to hospital is made by the individual. It is a subject of modelling assumption whether the frequency of doctoral visits afterwards, and the length of hospital stay are basically determined by the suppliers of health care or these are also decided by the patients. According to the seminal paper by Grossman (1972), health depends on "investment" in health. This "investment" is a function of medical care characteristics and other individual characteristics (like risky behavior) that might influence the efficiency of medical services. Hadley (2003) gives a review of the empirical results about these influencing mechanisms. As for morbidity there are no clear results about the effects of health care, but there is evidence that medical care can significantly increase longevity. Expenditure on consumption and on medical services are limited by income and wealth. The cost of medical services depends on several factors: on the type or quality of the service, whether the individual has private health insurance, and on the country-specific features of health care. I use two types of country-specific health care indicators: the ratio of public and total health spending, and measures of available health care resources. The first can capture the features

of the health insurance system, whereas the second indicates the abundance of health care facilities. More generous health insurance decreases health care costs, thus can increase health care demand - this is a moral hazard issue.

3 Health care financing structures

In this paper I analyze the effect of health care financing structure on health care utilization in eleven European countries. These are Austria, Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain, Sweden and Switzerland. These countries are all covered by the first wave of the SHARE data (the database is described in details in section 4), and the health insurance structures in these countries are comparable. Although Israel is also covered by the SHARE data, I exclude it from this analysis. The reason for excluding Israel is that this paper focuses on the effects of health care financing in Europe, moreover, the analysis refers to countries which are OECD members.

In all of the analyzed countries there is a mandatory health insurance system, but this insurance does not cover all the costs related to medical services. The main functions of PHI coverage are to cover the cost-sharing of medical services, and to finance those services which are not covered by the mandatory insurance scheme. In some countries (like Germany and the Netherlands) PHI can be the primary insurance for some groups of the population. The insurance system in Switzerland is different from the other countries in the sense that the mandatory health insurance is provided by private insurance companies. However, this mandatory private insurance is reported in the OECD data as public coverage.

France is also an outlier among the countries since the voluntary health insurance coverage in France is almost universal, and it is for reimbursement of co-payments for treatment in the statutory health care system. Although co-payments are general also in the other analyzed countries, such widespread coverage with complementary private health insurance can be observed only in France. In addition, the complementary insurance is provided free for those with low income in France.

In Table 1 I summarize the main characteristics of the health care financing structures in these countries based on Mossialos - Thomson (2004), OECD (2004), and Thomson et al. (2009).

4 Data

The database I use in the empirical analysis is the first wave (year 2004 observations) of the Survey of Health, Ageing and Retirement in Europe (SHARE), release 2.3.0.² It is a panel database (the second wave has been released in November 2008), covering individuals aged 50 or over, and their spouses. The database covers over 30 thousand individuals from twelve countries, the country coverage of Wave2 data is even wider. Although the sampling design varies across the participating countries, probability sampling is applied in each country. In this paper I estimate cross sectional models based on Wave1.³ The macro

²This paper uses data from SHARE release 2.3.0, as of November 13th 2009. SHARE data collection in 2004-2007 was primarily funded by the European Commission through its 5th and 6th framework programmes (project numbers QLK6-CT-2001-00360; RII-CT-2006-062193; CIT5-CT-2005-028857). Additional funding by the US National Institute on Aging (grant numbers U01 AG09740-13S2; P01 AG005842; P01 AG08291; P30 AG12815; Y1-AG-4553-01; OGHA 04-064; R21 AG025169) as well as by various national sources is gratefully acknowledged (see <http://www.share-project.org> for a full list of funding institutions).

³Although the data from the second wave of SHARE is available, I do not use that in this study. The main reason is that there is no direct question about private health insurance coverage in wave2, only the change in health insurance status is asked, which is not specified to private insurance. Moreover, there is only little variation in public health expenditure ratio along time in each country, which also makes panel estimation difficult.

	PUBLIC HEALTH INS.	COST SHARING	PRIVATE HEALTH INS.
AUSTRIA	Almost universal coverage	Applies to most services, exemptions: low-income pensioners, people with chronic health problems	Mainly for faster access, and reimbursement of hospital charges
BELGIUM	Almost universal coverage	Applies to most services, lower rates for those below income threshold	Mainly coverage of inpatient charges, and better inpatient care
DENMARK	Universal coverage	Few cost sharing arrangements, financial assistance: below income threshold, chronic health problems	Reimbursement of cost sharing, access to private care
FRANCE	Almost universal coverage	30% of fee for outpatient services, 20% for inpatient services	Coverage of co-payments
GERMANY	88% coverage; exemptions: civil servants, high-earners, self-employed	Cost sharing for pharmaceuticals, outpatient care, limited to inpatient care	Mainly for specialist care, dental care, luxury services
GREECE	Universal coverage, but membership in occupation-based HI fund required	Cost sharing for pharmaceuticals, outpatient care, reductions: chronic health problems, low income, pensioners	Minor role, reimbursement of charges
ITALY	Universal coverage	Cost sharing for pharmaceuticals, outpatient care, exemptions: age 65+, low income, chronic health problems	Minor role: coverage for cost sharing, for excluded and private services
THE NETHERL.	Prior 2006: high earners excluded (ca. 28%)	Cost sharing for some services (not for GP, specialist, hospital care), and for some pharmaceuticals	Primary for high earners, supplementary: dental care, luxury services
SPAIN	Almost universal coverage (0.5% not covered - high earners)	Cost sharing for pharmaceuticals, medical aids, exemptions: age 65+, chronic health problems	Supplementary role: private care, provider choice
SWEDEN	Universal coverage	Cost sharing for most health services, but with capped amount	Minor role: coverage for co-payments, faster access, private care
SWITZERLAND	Mandatory private HI	Cost sharing for pharmaceuticals, outpatient and inpatient care	Supplementary PHI: provider choice, luxury services

Table 1: Health care financing structure in the analyzed countries

health expenditure and health care resource indicators come from OECD and Eurostat statistics. The overall number of individual observations used in the estimations is 24.8 thousand. For the sake of simplifying the calculations, I use unweighted data, and for the monetary variables (income, value of main residence) I use the mean of the five imputations provided by SHARE. This latter simplification causes a slight downward bias in the standard error estimates, but does not affect the conclusions about the effect of health care financing on utilization.

For the included countries I analyze the effects of public health expenditures on health care demand, jointly with the demand for, and effects of private health insurance. Although my focus is on the effects of public expenditures, it is important to consider the PHI as well, since voluntary PHI is likely to be endogenous in a health care demand model.

I define private health insurance coverage as having any type of private or voluntary private health

insurance. Although there are questions in the SHARE about the services the private health insurance provides, I decided not to use these because of the following reasons. First, the definitions of these insurance categories vary across the country-specific questionnaires. Second, it would be difficult to separate the partial effects of the certain insurance types, since those are not exclusive categories, and the individuals can have such insurances that provide more service types. Moreover, in some insurance categories there are very few observations. However, I differentiate two categories of PHI: primary (substitutive) and supplementary. I categorize PHI as primary insurance if the individual has PHI but is not covered by publicly funded insurance. Such private insurance is prevalent in the Netherlands and also in Germany. In the Netherlands the high-earners are excluded from the public insurance. In the SHARE sample 36% of the individuals living in the Netherlands reported not having basic public health insurance coverage. These people have private primary coverage. In case of Germany, high-earners, self-employed people and civil servants might not be covered with the basic public insurance (10% of the sample). PHI is defined as supplementary if the individual has PHI in addition to public health insurance coverage⁴.

In principle, the generosity of the public health insurance scheme should not influence the health care demand of those who are not covered with public insurance. However, the measure of generosity I use in this paper (share of public health expenditures within total health expenditures) is sensitive to the coverage rate within the population, not only to the required co-payments. Therefore in order to estimate the effect of public expenditures, the total sample should be used, not only those who are covered with the public insurance.

Paccagnella et al. (2008) analyze in details the voluntary PHI coverage of people aged 50+ using the SHARE data. Estimating country specific probit models for insurance coverage shows that higher education and income generally increase the likelihood of insurance coverage, whereas age decreases that. The type of last employment and workplace, and the insurance status of the spouse also affect the PHI coverage. Paccagnella et al. (2008) point out the effect of employment status, but firm size also seems to have an influencing factor, although not in all countries. The predominant type of PHI also varies across countries, for example in Austria it is the insurance for hospital care, in the Netherlands the dental care insurance, whereas in Spain the insurance that provides direct access to specialists.

The dependent variables analyzed refer to the last 12 months before the interview. These are the number of times seeing or talking to a general practitioner (GP), and the number of nights spent in hospital. In addition, I estimate the model also for doctoral care other than visits to general practitioners, so as to check if the influencing mechanisms are different for visits to general practitioners and to specialists.⁵ When estimating the number of hospital nights or doctoral visits I exclude those observations where it is larger than 50. The first reason for this exclusion is theoretical: the underlying utility maximization model might not be valid for those in the worst health condition. Reporting high utilization can indicate critical health condition. The second reason is related to the data. In case of some included countries the SHARE data excludes individuals living in institutions for elderly. If these people are generally in worse health condition than the ones not living in such institutions, then the data is not representative for those with severe health problems. In addition, the number of doctoral visits is capped at 98 in the questionnaire, which implies an artificial "spike" (81 observations) at the maximum point of the distribution of doctoral visits. Cutting

⁴The aim of this terminology is compactness. In fact, supplementary PHI includes not only such health insurance contracts which supplement the primary insurance (cover services out of the coverage of the primary insurance), but also which complement that (finance co-payments for the insured health services).

⁵Nursing home stay is not analyzed because of few number of such observations, and no reliable estimation could be made about the effect of public health spending and of long-term care insurance. Dental visits are also not modelled, since there is no information in the SHARE data about the number of such visits.

the sample at 50 reported hospital nights, general practitioner or specialist visits implies the exclusion of less than 1% of the observations. Nevertheless, I make a robustness check with respect to this restriction in section 5.2.6.

Some descriptive statistics of the variables used in the estimations are presented in Appendix B. In this sample 38% of the individuals have some kind of PHI - for 33% it is supplementary, for 5% it is primary. As for the medical services used: 13% have been in hospital, 85% have visited a general practitioner, and 39% have visited a specialist. The average number of nonzero nights spent in hospital is 9.4, of nonzero GP visits is 5.4, and of nonzero specialist visits 3.9.

In Appendix B I also present a table of country-level averages of PHI coverage and health care statistics. There are large differences in supplementary PHI coverage rates (ranging from 5 – 6% in Greece and Italy to 83% in France). Primary PHI is relevant only in Germany and the Netherlands. The cross-country variation in the ratio of people reporting specialist visits or hospital stays is not negligible, but that is relatively small for GP visits. The standard deviation relative to the mean is around 25 – 30% for reporting hospital stays and specialist visits, but only around 8% for GP visits. The average number of nonzero general practitioner visits and the average length of hospital stays also show cross-country variation, here it is the number of GP visits for which the relative standard deviation is the highest. The average length of reported hospital stays is the largest in Germany (12), the average number of nonzero GP visits is the highest in Italy and Spain (8), whereas the highest average number of specialist visits can be observed in Greece (6). On the other hand, all these three utilization statistics are the lowest in Sweden.

Finally, I also present a table in the Appendix about the distribution of health care expenditures across three groups of financing agents: general government, private insurance, and private households. Unfortunately, these statistics are not available for Greece and Italy. Although there is a strong positive correlation between the PHI coverage rate and the ratio of health expenditures financed by private insurance, higher rate of coverage does not necessarily mean more reliance on funding by private insurance. For example, while the coverage rate with PHI in France is almost twice as high as in the Netherlands, the percentage of health expenditures financed by private insurance is higher in the Netherlands than in France. These deviations reveal the varying role of PHI across the countries analyzed.

5 Model estimation

5.1 Empirical considerations

A key modelling question is whether the partial effects of exogenous variables are the same across countries. Bago d’Uva - Jones (2009) reject the equality of income and education effects on health care utilization across European countries. However, the assumption of equality is needed in estimating the effect of country-specific health care financing and supply indicators, and this way the estimated coefficients can be interpreted as average effects. For supplementary private health insurance I estimate also only an average effect in the analyzed countries. On the other hand, I allow the effect of income and wealth on utilization to be country-specific. The price level of health care services relative to the price of other goods might vary across countries, these differences can be captured through the varying effect of income and wealth on utilization. The liquidity of certain wealth components, thus also their effect on health care utilization might also vary across countries.

A health care utilization model which motivates my empirical specification is provided in Appendix A, and has been also discussed in section 2. It is based on utility maximization, and merges two categories

of health demand models: those where the utilization is a result of a single decision, and those where the decision is made in two stages. The reason behind these two types of models is that many people do not utilize health care at all, and the decision about any utilization can be modelled separately from the positive amount of utilization.

A seminal theoretical model about health care demand is of Grossman (1972), in which health is a durable good, its "depreciation" is influenced by medical care. In his model the utilization of medical care is an individual decision. Most empirical health care models include a rich set of regressors to capture the health, and health production characteristics. This latter can include the price of health care, and standard socio-economic variables that affect availability of services, tastes, preferences. Such empirical models for health care demand are applied among others by Hunt-McCool et al. (1994) and Gibbons - Wilcox-Gok (1998). This strand of the literature follows the consumer theory approach. The other approach is based on the principal-agent set-up, where the initial contact is decided by the patient, but afterwards the utilization is determined by the physician. In the following I compare the results based on these two types of approach.

Deb -Trivedi (1997) give a summary of previous results about the determinants of medical care demand: one-step models generally estimate positive effect of health insurance coverage on medical care usage. A detailed discussion about econometric issues in estimating medical care usage models is given by Jones (2000). Basic issues are that the dependent variable (e.g. number of doctoral visits) is usually not continuous, there is a large number of zero observations, which can be modelled with one-step or two-step (selection) models, and there are usually measurement problems as well (e.g. imperfect measures of health or of the exact nature of health service).

In my empirical analysis I account for the potential endogeneity of supplementary PHI, and also for the large number of zero observations. This implies a count data model including two endogenous dummy variables, one for PHI coverage, and one for endogenous sample selection (positive outcomes). I extend the empirical model in a stepwise way, and compare the estimation results based on the various specifications.

As a first step, I assume that health care utilization is the result of a single decision - assume negative binomial distribution of the utilization variable, and treat supplementary PHI as exogenous. I use this specification as a benchmark model. Secondly, I follow the two-stage residual inclusion (2SRI) estimation method suggested by Terza et al. (2008). Here I treat the supplementary PHI as endogenous, and the health care utilization is still modelled in a single stage, assuming again negative binomial distribution. The third approach - which I call hurdle model - follows the method applied by Greene (1995). Here the utilization and the amount of utilization is modelled in two stages, and the supplementary PHI indicator is considered as endogenous only in the first stage. In this version of the model the number of visits and length of hospital stays are determined by the physician, and he does not take into consideration such unobserved effects which might have influenced the earlier decision on PHI coverage. The predetermined nature of insurance coverage, and the role of the physician in determining utilization can strengthen the exogeneity assumption of the private health insurance indicator. Finally, I estimate a selectivity model where the PHI coverage is endogenous also in the second stage. This approach requires the usage of trivariate distributions, and I apply limited information maximum likelihood estimation.

5.1.1 Benchmark model

As the benchmark case, I assume that health care utilization is a one stage decision, and supplementary PHI coverage is exogenous in this decision. Since there is a large ratio of zero observations among the reported numbers of hospital nights and of doctoral visits, assuming Poisson distribution would be problematic. I

assume negative binomial distribution, which allows overdispersion, and fits the data indeed relatively well.⁶

The benchmark utilization model is the following:

$$E[Y_{ji}|X_i, PHI_i, \varepsilon_{1ji}] = \exp(X_i\beta_{1j} + \gamma_{1j}PHI_i + \varepsilon_{1ji}), \quad (1)$$

where index i refers to individual i , and $j = 1, 2, 3$ differentiate the parameters and variables according to the dependent variable. Y is either the number of doctoral visits (GP and specialist visits) or hospital nights, PHI indicates the coverage with supplementary private health insurance, and X is a vector of variables including a rich set of socioeconomic and country specific health care indicators that might influence health care utilization through costs, potential benefits, and preferences. In particular, X includes age (cohort effects), gender, marital status, dummy variable for having children, log net income (household-level gross income divided by household size, average of imputed values used, minus the reported health insurance payment⁷), log value of main residence (divided by household size, average of imputed values - to capture wealth effects), education (ISCED codes 3-4 and 5-6 are merged to avoid the problem of too few observations in a category), employment status, indicators of the current employment as civil servant, public sector employee or self employed, living area and smoking dummies (as proxies for health behavior), having primary private health insurance, country specific health care indicators, and three health measures. An indicator of living in one of the Southern countries is also included in the model. In addition, in the general practitioner and specialist care utilization equations a dummy variable of the partner's utilization is also used as regressor. This variable can indicate attitudes towards health services, and utilization by the partner can also reduce the individual cost of contacting a physician.⁸ The effects of income, wealth, and primary PHI (relevant only in Germany and the Netherlands) are allowed to be country-specific. A constant term is also included in X - in the following equations the constant term is always implied among the regressors.

Three groups of health measures are included among the regressors. The first group consists of indicators of chronic health problems specified in the SHARE data.⁹ The second group indicators are selected problems with activities of daily living (ADL).¹⁰ The third group are indicators of symptoms the respondent reports.¹¹ These are binary variables, and can reveal need for hospital or doctoral care. I decided not to include indicators of health in general, because such subjective measures are likely to be endogenous in health care demand models, due to reverse causality. Objective health indicators are considered as exogenous: these reflect long-term health problems, the health care utilization on the other hand refers to the last year - I assume that there is no reverse causality to health status within one year. This assumption is the strongest for the chronic health problems data: the here applied survey questions on health problems ask about having

⁶A simple way to check the distributional assumption is using the *nbvargr* command in Stata, written by Philip B. Ender. Moreover, based on Gourieroux et al. (1984), if the mean is correctly specified, the maximum likelihood estimation gives consistent results even if the negative binomial distribution assumption does not hold.

⁷Since PHI is pre-determined in this model, it is reasonable to subtract its costs from the disposable income measure. I replace the net income to one for those where its calculated value is zero or negative (there are 85 such observations in the sample used). The median value of annual payments for private health insurance contracts is 417 EUR, the mean is 824 EUR among those in the sample who report any type of PHI coverage.

⁸If the partner's utilization would influence the utilization decision of both members of the couples then this indicator would be endogenous. I assume that for one member the utilization is determined by the own health condition and preferences, and this utilization might influence the decision of the spouse. I.e. the utilization by the couple is not a joint decision but a sequential decision.

⁹These conditions are: heart attack, high blood pressure, high blood cholesterol, stroke, diabetes, chronic lung disease, asthma, arthritis, osteoporosis, cancer, stomach ulcer, Parkinson disease, cataracts, hip or femoral fracture.

¹⁰These include difficulties with dressing, walking across a room, eating, bathing, getting in or out of bed, and using the toilet.

¹¹The specified symptoms are: pain in a joint, heart trouble, breathlessness, persistent cough, swollen legs, sleeping problems, falling down, fear of falling down, dizziness, stomach problems, and incontinence.

ever been diagnosed, and not about the current condition. Although the reported symptoms refer to the current or recent health condition, these are likely to indicate permanent health problems.

The country-specific variables among the regressors are the ratio of public health expenditure to total health expenditure (this indicator is presented in Table 2 in section 5.2.1), and indicators of health care resources (Eurostat and OECD data). The availability of health care resources might influence the price of health care relative to other goods.

ε_1 is a latent heterogeneity term, it is assumed that $\exp(\varepsilon_1)$ has gamma distribution. ε_1 includes unobservables which influence health care demand, but are independent from the regressors. These are basically such specific health characteristics which are not captured by the included health measures, but can also be other factors like being acquainted with a physician.

5.1.2 Two-stage residual inclusion

The assumption that PHI coverage is exogenous in the health care demand model might be unrealistic, even if it is considered to be predetermined. Time-invariant but unobserved taste shifters might be correlated both with supplementary PHI coverage and health care utilization. If supplementary PHI is endogenous in equation (1) then the consistency of the estimation is violated. The 2SRI estimation is applicable if utilization is still modelled as a one stage decision, but supplementary PHI is an endogenous binary regressor. Primary PHI coverage is not considered as endogenous, since that is basically the consequence of exogenous health insurance policies.

The 2SRI method is an implementation of instrumental variables method in nonlinear models. It is applicable when there are such regressors in a nonlinear model that are correlated with unobserved (latent) variables, and these unobservables also influence the outcome variable. This approach is widely applied in empirical models in health economics (for a list of citations see Terza et al. (2008)). An alternative to the 2SRI method could be the two-stage predictor substitution, but Terza et al. (2008) show that the later is generally inconsistent. However, provided that there are appropriate instruments for the endogenous regressor, the 2SRI method is consistent.¹² I apply maximum likelihood estimation in both stages. According to Cameron - Trivedi (2005), the consistency of two step m-estimation requires that the parameters in the first stage are estimated consistently, and the second stage parameter estimates with first stage parameters known would be consistent.

The first stage is a consistent estimation of the model for the endogenous regressor. The supplementary private health insurance coverage (*PHI*) of individual i is determined the following way:

$$\begin{aligned} PHI_i^* &= Z_i\alpha + \nu_i \\ PHI_i &= 1(PHI_i^* > 0). \end{aligned} \tag{2}$$

The variables included in vector Z are the following: age, gender, marital status, having children, the logarithm of gross income per capita in the household, the logarithm of the value of the main residence, education level, living area, and the country-specific health care system indicators. The instruments for PHI coverage included in vector Z are firm size (number of people employed at the current or last job) and last employment status indicators both for the individual and for the spouse. The reason for excluding smoking indicators and health measures is that PHI is treated as predetermined, thus health shocks and current

¹² Alternative estimation methods could be to use the full-information maximum likelihood or two-stage method of moments estimation suggested by Terza (1998).

health behaviors might not influence coverage.¹³ The aim with this specification is to include variables that can indicate individual preferences, costs of health care, and benefits related to supplementary PHI coverage, keeping in mind that the decision on coverage was made earlier. ν includes unobserved factors influencing supplementary PHI coverage (e.g. financial knowledge, risk taking preferences), and is assumed to have standard normal distribution, thus equation (2) implies a probit model. The model is estimated with maximum likelihood.

The identifying instruments of supplementary PHI are the indicators of the last employment: the number of people employed at the current or last job ("firm size" categories, being zero if self-employed or not applicable), and if in the last job was public employee, civil servant or self-employed. Occupational status can have an influence on PHI coverage, as it can be that the insurance is contracted through or supported by the employer, or different insurance regulations hold for the self-employed or civil servants. Paccagnella et al. (2008) document that in most countries covered by SHARE, supplementary PHI coverage is predominant among employees of larger firms. Mossialos - Thomson (2004) also report that group policies, i.e. voluntary PHI purchased by groups (typically employers) have a major role in many European countries. The availability of group policies varies with firm size. The identification is based on the assumption that only current employment indicators influence the utilization decisions, whereas the indicators of the last job influence insurance coverage. Similar identification strategy is applied by Jones et al. (2006) and Paccagnella et al. (2008). I also include the indicators of the spouse's employment, which are used as proxies for the spouse's insurance coverage.¹⁴ If the spouse is covered with PHI it can reduce the cost of contracting an insurance, or can also decrease the demand for PHI if the insurance covers family members.

I analyze the same dependent variables as under the benchmark model, and again assume that these have negative binomial distribution. Following the 2SRI estimation proposed by Terza et al. (2008), the first stage is estimating the probit model of equation (2), and the second stage is estimating the negative binomial models for the outcome variables, where both the residual from the first stage model and the endogenous explanatory variable are included as regressors:

$$E[Y_{ji}|X_i, PHI_i, \hat{u}_i, \varepsilon_{2ji}] = \exp(X_i\beta_{2j} + \gamma_{2j}PHI_i + \delta_j\hat{u}_i + \varepsilon_{2ji}). \quad (3)$$

The notations follow that of equation (1). \hat{u} is the first stage residual: $\hat{u}_i = PHI_i - \Phi(Z_i\hat{\alpha})$, where $\Phi(\cdot)$ is the cumulative standard normal distribution function, and $\hat{\alpha}$ indicates the estimated value of the parameter vector from the probit model. If PHI is exogenous in the j th health care utilization model then δ_j should equal zero. ε_2 includes unobservables (heterogeneity components) which are independent from the included regressors.

Since in model (3) the estimation results from the first-stage probit model are used, the standard error estimates should be appropriately adjusted. This is done based on Greene (2003), the details are presented in Appendix C.

¹³This statement is true if health shocks are independent from pre-existing health conditions. Pre-existing conditions influence coverage, since those are generally excluded from voluntary PHI cover (see Mossialos - Thomson (2004)). Analyzing the effects of long-term illness measures on PHI coverage is out of the scope of this paper, and would also require additional data (e.g. observations from the date of contracting PHI).

¹⁴Although information on the PHI coverage of the spouse is available, including that as a regressor would cause endogeneity bias.

5.1.3 Hurdle model

The third approach is applying two-stage (hurdle) modelling for the health care utilization variables. Two-stage modelling is a standard approach in modelling health care demand, see e.g. Zimmerman Murphy (1987), Pohlmeier - Ulrich (1995), and Werblow et al. (2007). The underlying assumption is that separate processes drive the probability of making any doctoral visits, and the exact number of visits (similarly for hospital stays).

The modelling assumption that I make here is that individuals decide on whether to visit a physician or go to hospital, but the frequency of visits and length of hospital stay are decided by the physician. As described also in Appendix A, the physician is considered to take into account all the observable factors that might influence the benefit and cost of the potential treatment. If I assume that these observables are included among the regressors, then supplementary private health insurance is endogenous only in the first stage. The exogeneity of supplementary PHI in the second stage is reasonable if unobserved preferences influencing both health insurance status and health care demand have a role only in determining the decision on any doctoral visit or hospital stay.

The first stage equations model the supplementary PHI coverage together with the probability of having any doctoral visits, specialist visits or hospital stays (Pos_Y_j).

$$\begin{aligned} PHI_i^* &= Z_i\alpha + \nu_i \\ PHI_i &= 1(PHI_i^* > 0) \end{aligned} \tag{4}$$

$$\begin{aligned} Pos_Y_{ji}^* &= X_i\beta_{3j} + \gamma_{3j}PHI_i + \varepsilon_{3ji} \\ Pos_Y_{ji} &= 1(Pos_Y_{ji}^* > 0). \end{aligned} \tag{5}$$

The regressors included in Z and X are the same as used in equations (2) and (3). Since some unobservables might affect both the supplementary PHI coverage and the decision on health care utilization, PHI can be endogenous in equation (5), hence the error terms ν and ε_3 can be correlated. Assuming that ν and ε_3 have bivariate normal distribution with zero means and unit variances, these two binary models form a bivariate probit model.¹⁵ This model handles the likely endogeneity of private health insurance in equation (5). The method of multivariate probit estimation in similar medical care demand framework is also applied by Gibbons - Wilcox-Gok (1998). If the exogeneity assumptions hold (Z and X are exogenous in equations (2) and (3)), the maximum likelihood estimation of the bivariate probit models gives consistent estimates. Moreover, based on the results of Gourieroux et al. (1984), violation of the normal distribution assumption does not affect the consistency of parameter estimates.

The nonzero number of doctoral visits and hospital nights are modelled with negative binomial regression models. It follows from the modelling assumptions that health preference indicators that do not influence the potential benefit or money cost (relative to individual resources) of treatment should have an effect only in the first stage decision. For inpatient care utilization the living area is considered as such variable which influences the probability of having been in hospital, but not the length of the stay. Living area can indicate the availability of inpatient care, and the inclination of going to hospital, but it is not likely to influence the length of the treatment. For outpatient care utilization the indicators of the spouse's visit to GP or specialist are excluded from the second stage model. These indicators can influence the propensity to visit

¹⁵To estimate the bivariate probit models, the *mvprobit* Stata module is used, written by Cappellari - Jenkins (2006b).

a physician. but not the frequency of visits afterwards. The second stage models have the following form:

$$E[Y_{ji}|\tilde{X}_i, PHI_i, \varepsilon_{4ji}] = \exp(\tilde{X}_i\beta_{4j} + \gamma_{4j}PHI_i + \varepsilon_{4ji}) \text{ if } Pos_Y_{ji} = 1, \quad (6)$$

where $\exp(\varepsilon_4)$ has gamma distribution, and \tilde{X} is the same as X , except for the exclusion restrictions. If the ε_4 unobserved heterogeneity term is independent of ν and ε_3 , then equation (6) can be consistently estimated with negative binomial regression (provided that \tilde{X} and PHI are also exogenous). However, it is likely that there are some unobserved individual characteristics that jointly influence the outcome variables. For example, omitted health problem measures which are observed by the physician might be included both in ε_3 and ε_4 .

I follow the procedure suggested by Greene (1994) and Greene (1995) for correcting the selectivity problem in Poisson and negative binomial models. This is the "mimic" of the Heckman procedure, with the inclusion of the inverse Mills ratio. The potential pitfalls are discussed by Greene (1995), however, he shows that this simple procedure is an approximation to methods suggested by other authors.

The estimated negative binomial models become (instead of equation (6)):

$$E[Y_{ji}|X_i, PHI_i, \varepsilon_{4ji}, M_Y_{ji}, Pos_Y_{ji} = 1] = \exp(\tilde{X}_i\beta_{4j} + \gamma_{4j}PHI_i + \varepsilon_{4ji} + \varphi_j M_Y_{ji}), \quad (7)$$

where $M_Y_{ji} = \frac{\phi(X_i\hat{\beta}_{3j} + \hat{\gamma}_{3j}PHI_i)}{\Phi(X_i\hat{\beta}_{3j} + \hat{\gamma}_{3j}PHI_i)}$.

In these models the estimation results from the bivariate probit models are used, therefore the second-stage standard error estimates should be appropriately adjusted. This is done similarly as for the estimation procedure of section 5.1.2, the details are presented in Appendix C.

Arguments pro and contra estimating models like (7) are summarized by Jones (2000). The main potential problem is that for such selectivity models the results of Gourieroux et al. (1984) do not hold. Therefore the validity of distributional assumptions matters for the consistency of parameter estimates. The sensitivity of sample selection models to distributional assumptions is discussed e.g. by Arabmazar - Schmidt (1982). Because of these concerns, I present some robustness checks with respect to the distributional assumptions and to model specifications in section 5.2.6.

5.1.4 Limited information maximum likelihood model

As final specification I continue with the two-stage modelling of section 5.1.3, but relax the assumption that supplementary PHI is exogenous in the second stage. Unobserved individual characteristics might influence both PHI coverage and the amount of health care utilization, especially if the number of hospital nights or doctoral visits is not solely determined by the physician.

The first-stage equations that model PHI coverage and initial utilization decision are the same as in the hurdle model - equations (4) and (5). Formally, the equation describing the positive amount of utilization is also analogous to equation (6), but now the assumption about the heterogeneity term is different.

$$E[Y_{ji}|\tilde{X}_i, PHI_i, \varepsilon_{5ji}] = \exp(\tilde{X}_i\beta_{5j} + \gamma_{5j}PHI_i + \varepsilon_{5ji}) := \lambda_{ji}(\varepsilon_{5ji}) \text{ if } Pos_Y_{ji} = 1, \quad (8)$$

I assume that ν, ε_3 and ε_5 have multivariate normal distribution with zero mean and variance $1, 1, \sigma^2$, respectively. Under this assumption it is not true any more that Y has negative binomial distribution, however, the normality assumption simplifies the manipulation of the likelihood function with endogenous

bivariate regressor and selectivity. Similar assumption (normal heterogeneity) is applied e.g. by Terza (1998) and Greene (2001).

The contribution of the i th observation with nonzero utilization to the likelihood is

$$\begin{aligned} \Pr(Y_{ji}, Pos_Y_{ji} = 1, PHI_i = k | X_i, Z_i) &= \\ &= \int \Pr(Y_{ji}, Pos_Y_{ji} = 1, PHI_i = k | X_i, Z_i, \varepsilon_{5ji}) f(\varepsilon_{5ji}) d\varepsilon_{5ji} = \\ &= \int \frac{\exp(-\lambda_{ji}(\varepsilon_{5ji})) \lambda_{ji}(\varepsilon_{5ji})^{Y_{ji}}}{Y_{ji}!} \Pr(Pos_Y_{ji} = 1, PHI_i = k | X_i, Z_i, \varepsilon_{5ji}) f(\varepsilon_{5ji}) d\varepsilon_{5ji}. \end{aligned} \tag{9}$$

In the second step equation (8) has been used, and k equals 0 or 1.

$f(\cdot)$ is the normal probability density function with mean zero and variance σ^2 . The second term in the integral can also be expressed as a function of ε_{5ji} , using the first-stage bivariate probit estimation results, and the assumption of multivariate normality.¹⁶ In order to simplify the estimation procedure I follow the limited information maximum likelihood (LIML) procedure - I estimate the bivariate probit model of equations (4) and (5) in the first stage, and use these estimation results as known in the second stage.

There is no closed form solution for the integral of equation (9), but it can be approximated by simulation. I apply the maximum simulated likelihood procedure as described by Cameron - Trivedi (2005). In the simulations I use 100 draws from the Halton sequence with prime number 7.¹⁷ Due to the two-stage estimation procedure the estimated standard errors of the second stage have to be adjusted again, the details of this procedure can be found in Appendix C.

5.2 Estimation results

5.2.1 PHI demand

The two basic functions of supplementary PHI coverage is to cover the costs of health care not financed by the public health insurance, and to make high quality services affordable. Therefore the generosity of the public health insurance, and the expected utilization (attitudes towards medical care) are likely to influence the demand for supplementary PHI. Analyzing the effect of public health spending on PHI coverage is reasonable, since the part of health expenditures not financed by the general government can be financed either by private insurance companies or by out-of-pocket expenditures of the households (as can be seen from the third statistical table of Appendix B). Based on the raw data, as presented in Table 2, it is not possible to find clear evidence for this effect. The country-specific private health insurance coverage ratio is negatively correlated with the ratio of public health expenditure within the total. On the other hand, there is strong positive correlation between the private insurance statistics related to the whole and to the aged

¹⁶Conditional on ε_5 , the joint distribution of ν and ε_3 is bivariate normal. The mean is

$$\frac{\varepsilon_5}{\sigma^2} \begin{bmatrix} Cov(\nu, \varepsilon_5) \\ Cov(\varepsilon_3, \varepsilon_5) \end{bmatrix},$$

and the covariance matrix is

$$\begin{bmatrix} 1 - \frac{Cov(\nu, \varepsilon_5)^2}{\sigma^2} & \\ Cov(\nu, \varepsilon_3) - \frac{Cov(\nu, \varepsilon_5)Cov(\varepsilon_3, \varepsilon_5)}{\sigma^2} & 1 - \frac{Cov(\varepsilon_3, \varepsilon_5)^2}{\sigma^2} \end{bmatrix}.$$

¹⁷For producing the Halton draws I use the Stata code *mdraws* written by L. Cappellari - S. P. Jenkins. Cappellari - Jenkins (2006a) also discuss the advantages of Halton draws in MSL estimation.

Similar estimation technique is applied by Deb - Trivedi (2006): they estimate a negative binomial model with endogenous multinomial treatment.

50+ population (the second column in the table refers to voluntary PHI coverage ratio within the whole population).

	Public/Total (%)	% total population with substitutive, supplementary or complementary VPHI	% 50+ population with PHI
Au	75.7	31.9	23.3
Be	72.9	~47.1	76.0
Dk	83.8	28.0	36.3
Fr	79.3	94.0	84.2
Germ	77.0	18.0	21.6
Gre	59.1	10.0	5.2
It	76.0	15.6	5.6
Nl	64.4	~84.7	81.8
Sp	70.5	12.0	9.2
Swe	81.8	~1.25	9.0
Swi	58.4	.	32.7
data source	OECD	Mossialos - Thomson (2004), Table 5.	SHARE, Wave1, sample used

Table 2: Basic health insurance statistics, year 2004

I estimate the probability of PHI coverage based on equations (2) and (4). As expected, the simple probit and bivariate probit estimation results are almost equal, as there are no endogeneity issues. The estimated coefficients and their significance are reported in the first column of the table in Appendix D.1.

Based on the pooled estimation results, the probability of coverage decreases with age, but increases with income and wealth. The effect of education is positive in most of the countries, however in the pooled sample the average effect is negative. Both the dummy of civil servant and self-employed status at the last job have positive sign, and are significant. Although the estimated likelihood of PHI does not increase monotonically with firm size, the highest (above 500 employees) firm size implies the highest probability of coverage, *ceteris paribus*. The firm size of the partner's last workplace and the partner being civil servant or self-employed also increase the likelihood of PHI coverage. These results suggest that the partner's coverage with PHI increases the probability of the own insurance coverage. The significance of the workplace indicators suggests that these variables can be reasonably used as instruments for PHI coverage.

The coefficient of public/total health expenditure is significantly negative. 1 %point higher public health expenditure ratio within the total decreases the probability of supplementary private insurance coverage with 0.2 %points at the average, *ceteris paribus*. The negative effect is reasonable: in countries with more generous social security systems there is less need for private health insurance.

As for the health care demand estimates, in the next points I just briefly summarize the estimation results and provide some sensitivity analysis. The comparison and interpretation of the results are provided in section 6.

5.2.2 Benchmark estimation results

The estimated coefficients of the benchmark model are reported in Appendix D.1. The partial effect of public health spending ratio is positive for all three health services, however for specialist care it is insignificant at 10% significance level. The partial effect of supplementary PHI is also positive, but it is insignificant for visits to general practitioners.

The indicators of health problems generally have positive coefficients in the health care utilization models, and utilization by the partner is estimated to increase the probability of outpatient care utilization.

5.2.3 2SRI estimation results

In this specification I treat the utilization as a result of a single decision, but supplementary PHI is considered as endogenous. The estimation results are reported in Appendix D.2. The standard errors are corrected for the two-stage estimation (coefficient estimates from the first-stage probit model are used in the second-stage nonlinear regressions), but this adjustment increases the estimated standard errors only slightly, and does not affect the significance of any parameter. The adjustment increases the standard errors generally by a magnitude of less than 10^{-10} . The adjustment of the standard error has a similarly small effect under the hurdle and LIML estimations.

If supplementary PHI is exogenous then the estimated coefficient of the first-stage residual should be insignificant (δ_j in equation (3)). The coefficient of the residual is significant in the model of all three health care categories, which indicates the endogeneity of PHI. The estimated coefficient of the residual is positive for GP visits, and negative for hospital nights and specialist visits.

The estimated effect of public health spending ratio is positive and of similar magnitude as under the benchmark model. For specialist care it is insignificant. The partial effect of supplementary PHI is much larger in absolute value than under the benchmark model. Its effect is negative for GP visits, but positive for hospital nights and specialist visits. These results show that assumptions about the exogeneity matter more for the estimated effect of PHI than of public spending, and PHI coverage decreases mainly the visits to general practitioners. As supplementary PHI can provide direct access to specialists, the negative effect is reasonable.

Finally, similarly to the benchmark model, the estimated effects of health problems are generally positive for all service types, and outpatient care utilization by the partner increases the own utilization of doctoral care.

5.2.4 Hurdle model estimation results

The hurdle specification follows the model described in section 5.1.3 - the utilization is modelled as a two-stage decision, and supplementary PHI is considered to be endogenous only in the first stage. The estimation results are reported in Appendix D.3. Again, the adjustment of the standard errors for two-stage estimation has only minor effect.

The first stage decision is about the utilization. The estimated coefficients of both the public health expenditure and supplementary PHI indicators are positive in these probit models, except for the estimated effect of public financing on GP visits. However, the effect of public health spending ratio is significant only for hospital care, whereas that of supplementary PHI is significant only for specialist care.

The estimated correlations of error terms in the bivariate probit models for PHI coverage and health care utilization are not significant for any of the three type of health care. This finding supports the exogeneity of PHI indicator, and suggests that estimating simple probit models of health care utilization, including PHI coverage as regressor could also provide consistent results. On the other hand, selectivity seems to matter in the negative binomial models, at least for inpatient care and GP visits - the inverse Mills ratio in equation (7) is significant in the hospital and GP care utilization model.

Although the exogeneity of supplementary PHI in the second-stage estimations can be questionable, an advantage of the here applied two-stage estimation method is that it can reveal the different effects of the

observables on the utilization decisions and on the amount of utilization. Relatively few (3,040) individuals report hospital stays in the sample used, which might partly explain why most coefficients are insignificant in the hospital nights model. The public health spending ratio has positive effect on all three types of services, but significant only for visits to general practitioners. Therefore it seems that more generous public health financing does not affect the propensity of visiting a physician, but increases the frequency of visits to general practitioners. The same is true for the effect of the number of physicians relative to the population. Similarly to the results of the other specifications, the partial effect of the relative number of hospital beds is positive also on outpatient care utilization. This indicates a supply-side effect, but its further investigation is out of the scope of this paper.

As for the estimated effect of supplementary PHI, there is no evidence based on the hurdle model that it would increase the amount of health care utilization. Moreover, it is estimated to have significant negative effect on the nonzero number of hospital nights and GP visits. This might indicate the utilization of higher quality of health services - this issue is further discussed under the results of the LIML model.

The coefficients of the health indicators are generally either insignificant (number of hospital nights) or significantly positive.

5.2.5 LIML estimation results

The first-stage utilization decision is modelled the same way as under the hurdle model, therefore this part of the analysis of section 5.2.4 applies here also. The second-stage estimation results are presented in Appendix D.4.¹⁸ In this specification supplementary PHI is allowed to be endogenous also in the second-stage of utilization decision. Similarly to the 2SRI and hurdle models, the adjustment of standard errors for two-stage modelling has only small effects. There is some evidence that PHI is endogenous in the second-stage decision on medical care utilization - the estimated correlation between the error term of the PHI model and the unobserved heterogeneity in the utilization model is negative for inpatient care (-0.41) positive for outpatient with value around 0.54 and 0.23. In addition, the first- and second-stage utilization decisions seem to be strongly negatively related in case of outpatient care.

The estimated effect of higher ratio of public health care financing is positive for hospital and GP care, but it is significant only for the number of visits to general practitioners. Just as in the hurdle model, the coefficients of health problem indicators are generally either significantly positive or insignificant. However, there are no clear results about the supply-side effects of health care resources.

The partial effect of supplementary PHI coverage varies across the three service types: it is significantly positive for hospital nights, significantly negative for GP visits, and negative but insignificant for specialist visits. These effects are different from the hurdle estimation results, thus it matters if PHI is treated as endogenous in the second stage of the utilization model. Since I use a single indicator of supplementary insurance, the interpretation of effects is not straightforward. The positive effect can be explained by loosening the budget constraint through lower out-of-pocket costs. The most likely reason for the negative effect on GP visits is the utilization of higher level health services. Nevertheless, the negative effect on the number of visits to specialists remains a puzzle. As for GP visits, PHI can provide direct access to specialists, thus might not affect or even decrease the number of doctor visits. For example, Pohlmeier - Ulrich (1995) find negative effect using German micro-level data, and explain that with institutional settings.¹⁹ A more

¹⁸Stata's maximum likelihood estimation procedure is applied, with techniques NR, BFGS, and DFP. Technique BHHH reported problems in the numerical calculations. Convergence is achieved in 15, 6, and 11 steps in the hospital care, GP care, and specialist care models, respectively.

¹⁹General practitioners in Germany have a gate-keeping function only for those who are not covered with private health

detailed analysis of the country-specific effects of PHI coverage on health care utilization is out of the scope of this paper.

5.2.6 Specification checks

How sensitive are the empirical results presented above to distributional assumptions? The descriptive statistics suggest that there is overdispersion in the outcome variables²⁰, hence the assumption of Poisson distribution might not be valid, and estimating negative binomial regression is reasonable. The validity of distributional assumptions can affect consistency in two-stage modelling. In addition, the exogeneity assumptions also influence the estimated coefficients of the variables of interest.

In Table 3 I present the coefficient estimates of the selected key variables of interest under four specifications. Here I consider health care utilization as a single decision, and treat supplementary PHI as exogenous. The first specification is the benchmark negative binomial regression (as presented in section 5.2.2). The second is the Poisson regression, which neglects overdispersion. The last two columns refer to robustness checks with respect to simplifying assumptions and to the selection of estimation sample. The coefficients in column (3) refer to the benchmark negative binomial specification, but allowing for country-specific effect of supplementary PHI. Finally, for the sake of analyzing the sensitivity to sample restriction, in the last column I repeat the estimation results of the benchmark negative binomial regressions without excluding the observations with the highest reported health care utilization (hospital nights or doctoral visits above 50).

		(1)	(2)	(3)	(4)
		Negative binomial	Poisson	Neg. binomial, country specific PHI	Neg. binomial, unrestricted sample
# hosp. nights	Public health exp./total	0.146***	0.126***	0.157***	0.133**
	Supplementary PHI	0.159*	0.049***		0.228**
# GP visits	Public health exp./total	0.040***	0.048***	0.040***	0.050***
	Supplementary PHI	-0.001	-0.011		0.003
# spec. visits	Public health exp./total	0.029	0.018*	0.031	0.025
	Supplementary PHI	0.093***	0.096***		0.051

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Benchmark medical care demand estimation results under various specifications

According to the results presented in Table 3, the count data models give estimates of similar magnitude for the public health spending coefficients. In all of these count data models the expected number of doctoral visits and hospital nights are modelled as exponential function of the regressors, therefore the coefficients can be compared. For all three types of health care the estimated effects of public health spending ratio are close to each other across the various specifications, and the coefficients remain significant for hospital care and GP visits. For specialist care this estimated effect becomes significant at 10% significance level under the Poisson model. If individuals reporting more than 50 visits are also included in the sample, the estimated effect of public financing becomes larger for GP visits, but smaller for hospital and specialist care. This indicates that for people in worst health condition the effect of public financing on hospital and specialist care utilization is smaller. The coefficient of the supplementary PHI is less robust to the alternative specifications.

insurance (as described in Pohlmeier - Ulrich (1995)).

²⁰In Poisson models overdispersion means that the mean of the observations is smaller than their variance.

Based on these results the negative binomial specification can be reliably used for analyzing the effects of public health care financing, keeping in mind that the model has limited validity for people in worst health condition.

As a second set of robustness checks, I simplify the LIML step by step, and check how sensitive are the results to changes in the empirical model. In column (1) of Table 4 I repeat the estimated coefficients of the health care financing indicators under the LIML specification, as discussed in section 5.2.5. In the next columns, where the unobserved heterogeneity term is assumed to have normal distribution, maximum simulated likelihood estimation method is applied in an analogous way as described in section 5.1.4. The results in column (2) correspond to the case when supplementary PHI is exogenous in the utilization models (i.e. $corr(\nu, \varepsilon_3) = 0$ and $corr(\nu, \varepsilon_5) = 0$ in the model of section 5.1.4). This modification does not affect the sign and significance of the coefficients of public health spending, but has a large effect on the estimated coefficients of PHI. For outpatient care the effect of PHI shifts upward, and becomes significantly positive for the care provided by general practitioners. The reason for this change in the PHI coefficients can be that supplementary PHI is positively correlated with such unobserved characteristics which increase the demand for health care (e.g. positive attitude towards physicians, or unobserved health problems). For inpatient care the coefficient of PHI becomes insignificant and negative if exogeneity is assumed.

Next, I assume not only that PHI is exogenous in the utilization decisions, but also that the first- and second-stage decisions on utilization are independent (i.e. $corr(\varepsilon_3, \varepsilon_5) = 0$ in the model of section 5.1.4). This simplification does not affect the sign of the public health spending coefficients, but it becomes significant for inpatient care, as can be seen in column (3) of Table 4. Such a simplification affects the magnitude of the estimated effect of supplementary PHI, thus treating the two decisions on utilization independent would be misleading.

Finally, I compare these last estimation results to the case when the unobserved heterogeneity term is assumed to have log-gamma distribution, hence the amount of utilization is described with a negative binomial model.²¹ The estimated effect of public health spending on hospital nights under this specification is close to that reported in column (3). For outpatient care there are some differences in the estimated coefficients, but for specialist care these effects are insignificant both under the normal and log-gamma distribution assumptions. However, for GP visits the magnitude of the estimated effect is larger under the log-gamma distributional assumption than under normality. This finding reveals that the distributional assumptions matter for the exact magnitude of the estimated effects.

It follows from this analysis that neglecting the correlations of unobserved terms affects the estimation results, thus applying the most sophisticated (LIML) model is reasonable. The estimated effect of PHI coverage is more sensitive to these restrictions than that of public financing. There is some evidence that the estimation results are sensitive to the distributional assumptions, which are needed for maximum likelihood estimation. Nevertheless, the negative binomial results are comparable to those when normal distribution is assumed for the heterogeneity term, and the sign of the main coefficient of interest (public health spending) is robust to these assumptions. Based on these considerations, the LIML model presented in section 5.1.4 remains the preferred specification.

²¹This specification is different from the benchmark model, since here only the positive outcomes are considered, whereas in the benchmark model the zero outcomes are also included.

		(1)	(2)	(3)	(4)
		LIML	Exog. PHI	Exog. PHI, two	Exog. PHI, two
		(normal)	(normal)	stages independent	stages independent
				(normal)	(log-gamma)
# hosp. nights	Public health exp./total	0.044	0.046	0.057*	0.062*
	Supplementary PHI	0.388**	-0.043	-0.003	-0.066
# GP visits	Public health exp./total	0.025**	0.026**	0.026**	0.042***
	Supplementary PHI	-0.415***	0.032*	0.022	-0.022
# spec. visits	Public health exp./total	-0.008	-0.012	-0.018	-0.005
	Supplementary PHI	-0.161	0.031	0.039	0.021

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: LIML estimation results under various specifications

6 Simulations

Using the results presented so far, it is possible to analyze to what extent can cross-country variation in public health spending contribute to the differences in health care utilization, and also to analyze how supplementary private health insurance coverage "typically" affects health care utilization. The influencing mechanism of public financing works through two stages: first, the likelihood of private health insurance coverage is affected, second, the demand for the three types of medical care is determined. My aim here is to interpret the magnitudes of the coefficient estimates from the nonlinear models, and to compare the results of the different estimation strategies. The point estimates of coefficients and correlations are used from these underlying models. For the income and wealth variables I use the average of the estimated country-specific coefficients.

The identification of the public health spending coefficient is based on the cross-country variation in public health spending ratios. It is questionable if these results can be viewed as policy simulations for the individual countries. Since the results are based on differences across countries, no reliable predictions can be made about how health care utilization would change in a given country if public health spending changes there. The results can rather show how public health spending can explain differences in usage of health services.

I analyze two scenarios. First, I simulate the effect of a 7.56 %point increase in the ratio of public health spending to total health expenditure, deviating from its median level, which is 75.7% (keeping the health care resources constant). The magnitude of this increase equals one standard deviation of the public financing indicator, and is comparable to "moving" from the Netherlands to Belgium or from Spain to Germany. This simulation is about the results of higher reliance on public financing in medical care. Second, I simulate the case when the public health spending ratio is unchanged, but the representative individual becomes covered with supplementary private health insurance. This can be the result e.g. of some policy decisions, like subsidizing PHI coverage, or can also be the result of liberalizing the health insurance market. In this second set of simulations I treat supplementary PHI as it were exogenous.

The outcome variables in these simulations are supplementary PHI coverage (only in the first case), and the utilization of the three types of medical services. These are compared to the basic outcomes of the models. I am interested in the sensitivity of the expected number of doctoral visits and hospital nights to the financing structure, therefore I do not analyze separately the utilization decision and amount of utilization in

the two-stage models. This analysis is done separately for men and women. All the other variables are fixed at their median levels (continuous variables) or modal values (categorical variables). This means e.g. that the simulations are done for individuals who are retired, live with spouse, have secondary education, live in small town, report to have none of the specified health problems, and have annual income of 14 th EUR. Since the effect of supplementary PHI coverage on the logarithm of net income is small²², and the estimated coefficients of log net income in the utilization regressions are close to zero, I neglect in the simulations the effect insurance premium payment due to PHI coverage.

Before analyzing the simulation results, I compare the model outcomes without policy changes to the aggregates observed in the data used (Table 5). Even though the outcomes at the medians should not be necessarily equal to any of these aggregates, the model outcomes generally lie between the data means and medians. The predicted utilization of health care under the LIML model is larger than under the other models, and approaches the data mean (in case of specialist care it predicts an even larger utilization than the observed mean for males).

	MALES					
	Benchmark	MODEL			DATA	
		2SRI	Hurdle	LIML	mean	median
Suppl. PHI coverage	0.18	0.18	0.18	0.18	0.33	0
# hospital nights	0.42	0.56	0.22	0.43	1.54	0
# doctoral visits	2.25	2.15	2.17	4.57	4.37	2
# specialist visits	0.61	0.70	0.41	1.35	1.48	0

	FEMALES					
	Benchmark	MODEL			DATA	
		2SRI	Hurdle	LIML	mean	median
Suppl. PHI coverage	0.18	0.18	0.18	0.18	0.33	0
# hospital nights	0.38	0.50	0.21	0.43	1.53	0
# doctoral visits	2.39	2.29	2.39	4.78	5.43	3
# specialist visits	0.70	0.81	0.49	1.53	1.78	0

Table 5: Comparison of simulation outcomes (exogenous variables at their medians or modes) and aggregates from the data

Now I turn to the results of simulating increasing public health spending relative to total health expenditure. The 7.56 %points higher public health spending ratio implies around 2 %points lower probability of supplementary PHI coverage for men, and 1 %point lower for women. This means that in countries where health care is financed from public sources to a higher extent, supplementary private health insurance coverage is less widespread among the elderly people. A possible interpretation is that lower expected out-of-pocket health expenditures decrease the demand for additional health insurance.²³

After raising the public health expenditure ratio, the simulated utilization increases for all three service types under each estimation method. In general these effects are small, but the magnitude varies depending on which estimation method is used. In the two-stage decision (hurdle and LIML) models higher public health spending rate is estimated to increase both the probability of utilization and the amount of utilization of inpatient care, for outpatient services the sign of the effect is different on the probability of utilization and

²²The difference between the median values of logarithm of income and net income among the individuals covered with PHI is 0.04.

²³This result is not self-evident, since in principle it would be possible that in countries with higher public financing share the PHI coverage rate would also be higher, and the relative magnitude of out-of-pocket health expenditures would be much lower.

number of visits. I analyze the effects of changing health care financing on the predicted number of hospital nights or doctoral visits, but I also calculate the percentage changes in utilization, because this way the varying initial values (as presented in Table 5) do not influence the comparisons across the models. The simulation results are reported in Table 6. Based on the coefficient estimates as discussed in section 5.2, the estimated effects of the financing indicators on utilization are generally significant, but the effect of public financing on specialist care utilization is insignificant.

The simulated increase in the number of hospital nights is around 0.4 – 1.2 under all specifications, which is a small effect in absolute terms. However, this implies a large, above 150% relative increase. The smallest relative effect is found based on the LIML model.

As for the number of GP visits, the predicted increase is around 0.6 – 0.9. In percentage terms the benchmark and 2SRI models predict the largest increase (35–37%), the LIML models the smallest (16–18%). For the specialist visits these differences are similar in relative terms, but much smaller in absolute magnitude. For this service type again the LIML specification predicts the smallest relative increase (17 and 21% for males and females), and the benchmark model the largest (25%). These findings imply that it matters for the estimated effects whether supplementary PHI is treated as exogenous in the utilization decisions or not, and if utilization is modelled as a one-stage or two-stage decision. One-stage modelling can overestimate the positive effect of public spending on outpatient care utilization. As for the two-stage modelling, if supplementary PHI is assumed to be exogenous in the second-stage decision then the positive effect of public generosity can be overestimated for hospital and GP care. However, all these effects are small in terms of the number of hospital nights or doctoral visits.

The simulated effects of supplementary private health insurance coverage on health care utilization are generally smaller than those of the above analyzed shift towards public financing. However, under the 2SRI and hurdle models PHI coverage is estimated to increase the utilization of specialist care more than the increasing public financing share. In the benchmark model, where PHI is treated as exogenous, small positive effects are found for hospital and specialist care. Based on the LIML model, which is the preferred specification, the sign of the estimated effects are the same but greater in magnitude. PHI coverage is found to increase the utilization of hospital and specialist care, but decrease the number of visits to general practitioners. The interpretation of these results is difficult due to the heterogeneous nature of PHI coverage. Nevertheless, the larger relative effect on specialist care than on GP care is in line with the utilization of higher quality of services.

The simulation results are summarized in Table 6. The table includes the values when the exogenous variables are fixed at their medians or modes. The simulation results are comparable to those of closely related papers, although exact comparison of estimated effects is not possible due to the various models and data used. There are mixed results in the literature about the effect of public financing on health care utilization, which results are typically based on country-level data. Using micro data I find small positive effects. This finding is comparable to the results of Hitiris - Posnett (1992) or Bolin et al. (2009), who claim that public financing and health institutions have small effect on health care demand. My estimations indicate an even smaller effect of supplementary PHI coverage on the health care utilization measures, but this finding is more sensitive to the specification used. The general finding in the literature is that PHI has positive but moderate effect on health care utilization. For example, using the RAND health insurance experiment data, Manning et al. (1987) show that medical care utilization is sensitive to the generosity of

	PUBLIC/TOTAL HEALTH EXPEND. INCREASED				SUPPL. PHI COVERAGE SET TO 1			
	Absolute changes		Relative changes		Absolute changes		Relative changes	
	males	females	males	females	males	females	males	females
BENCHMARK								
# hosp. nights	0.86	0.77	201.5%	201.5%	0.07	0.07	17.2%	17.2%
# gp visits	0.79	0.84	35.3%	35.3%	0.00	0.00	-0.1%	-0.1%
# specialist visits	0.15	0.17	24.5%	24.5%	0.06	0.07	9.7%	9.7%
2SRI								
# hosp. nights	1.13	1.01	200.7%	200.9%	1.05	0.94	187.7%	186.0%
# gp visits	0.79	0.85	36.9%	36.9%	-0.48	-0.51	-22.3%	-22.2%
# specialist visits	0.16	0.19	23.3%	23.3%	0.57	0.66	82.1%	81.4%
HURDLE								
# hosp. nights	0.44	0.40	201.8%	194.0%	0.03	0.02	13.9%	8.6%
# gp visits	0.63	0.77	29.2%	32.2%	0.13	0.11	5.9%	4.7%
# specialist visits	0.08	0.12	19.7%	23.9%	0.12	0.15	30.1%	30.5%
LIML								
# hosp. nights	0.68	0.65	158.4%	151.5%	0.23	0.20	54.0%	46.4%
# gp visits	0.71	0.86	15.6%	18.0%	-1.11	-1.19	-24.2%	-25.0%
# specialist visits	0.23	0.32	16.9%	21.1%	0.16	0.19	12.1%	12.7%

Table 6: Changes in simulated outcomes at the median (mode for discrete variables)

insurance plans, but they claim that the spread of health insurance can not explain the observed rise in medical expenditures. Using a U.S. survey data, Gibbons - Wilcox-Gok (1998) also show a positive, but moderate effect of supplemental PHI on the probabilities of outpatient and hospital care utilization.

Based on the simple theoretical health care utilization model presented in Appendix A, it is not straightforward in which groups of the population should changes in the health care financing matter more for health care utilization. For example, it might be that in the demand for doctoral care the changes in financing matters more for people with health problems, since additional care becoming available can contribute to the improvement of their health status. However, it can also be that the financing structure influences the demand more for healthier people, since their health care utilization is less imperative, therefore might be more responsive to out-of-pocket costs. The heterogeneity of this effect depends on the individual preferences, and on the budget constraints.

I repeated the above simulations for the same representative individual, except for having three types of health problems: high blood pressure, high level of blood cholesterol, and having pain in some joints. Based on these simulation results, the absolute effect of higher public financing share on GP care utilization increases with the selected health problems: those who report these health problems seem to increase the utilization to more extent than those who are healthier in this respect. Such heterogeneity in absolute effects is not unambiguous for inpatient and specialist care. Moreover, the relative effect of public health care financing on utilization is very similar for the representative individual and for the individual reporting these selected three health problems.

The main conclusions from these simulation exercises are that the modelling assumptions matter for the estimation of the effect of financing structure on health care utilization. However, it is a robust finding that higher public expenditure ratio increases the amount of utilization, but this effect is small in absolute terms.

The effect of supplementary PHI on utilization varies across the service types, there is some evidence for small positive effects on outpatient specialist and inpatient care.

7 Summary and further issues

In this paper I analyze the determinants of health care utilization in Europe among people aged 50 and above, focusing on the effect of public financing. The results are based on multi-country cross-sectional data. The main finding is that a greater share of public financing in health care expenditures has a positive, but small effect on health care utilization. Three categories of medical services are considered, and the positive effect is significant for inpatient and general practitioner care, but insignificant for outpatient specialist care. These findings are robust to modelling assumptions. The empirical results show that more generous public health financing decreases the demand for supplementary PHI. There is also some weak evidence that supplementary PHI can on average slightly increase the utilization of hospital and outpatient specialist care.

These estimated effects are compared under various modelling assumptions. Although the main conclusions about the effect of public health spending are robust to the specifications, the exact size of the estimated effects varies with the assumptions. Modelling health care utilization as a two stage decision generally decreases the estimated positive effect of higher public health expenditure. Due to the effects of unobservables, private health insurance coverage is likely to be endogenous in health care utilization models. In this paper I take into consideration this endogeneity also in the two-stage decision model, which I estimate with maximum simulated likelihood. Exogeneity assumptions about supplementary PHI influence not only the estimated coefficient of the private insurance indicator, but also the estimated effect of public health financing measure.

Some issues about the effects of public health spending and PHI coverage on health care utilization remain for future research. First, further robustness checks could be made through repeating similar estimations using the SHARE Wave2 data, assuming that private insurance coverage has not changed between the two waves. Although the country coverage of Wave2 is wider, such an extension is limited by the fact that the question about private health insurance is not included in the Wave2 questionnaire. Second, analyzing the utilization of public and private health care services is possible to some extent based on the SHARE data. Finally, using the panel nature of the SHARE database, health care utilization after health shocks could be analyzed. These findings could again be related to the health insurance status and to the country specific characteristics of the health care systems.

Appendix

A Modelling framework

The aim of the model presented here is to provide a theory how financing structure of health care affects the demand for health care services. This effect works through net health care prices - public financing and private health insurance coverage decrease the net out-of-pocket price of health care.

In a health insurance model the level of health expenditure is not exogenous, therefore it is not like a standard insurance model. Welfare loss from health insurance is discussed e.g. by Feldstein (1973). Here I treat health insurance as exogenous (public health insurance) or predetermined (private health insurance), therefore I do not discuss the self selection problem. I focus on the moral hazard issue: health insurance modifies the net price of health care, which can affect the demand for health care.

The model is for one type of medical care, e.g. for overall doctoral visits. Individuals maximize a deterministic utility function, which depends on consumption and health.²⁴ Medical care influences health, but current health also depends on pre-existing conditions. Health insurance causes a proportional decrease in the price of health care. Net income (Y_i , income net of paid insurance premium) is constant, and there are no saving or borrowing opportunities. The lack of borrowing opportunities can be a reasonable assumption for older individuals. Here I neglect wealth, which could broaden the consumption opportunities. Index i refers to the i th individual. The maximization problem is the following:

$$\begin{aligned} \max_{C_i, M_i} U(C_i, H_i) \\ p_i M_i + C_i &= Y_i \\ H_i &= f(H_{0i}, M_i) \end{aligned}$$

C_i denotes consumption, H_{0i} is the initial health level (indicating pre-existing conditions), whereas H_i is the health level after medical care. M_i measures medical care utilization (e.g. number of doctoral visits), and p_i is the net (out-of-pocket) price of medical care relative to the price of other goods. The price of other goods is normalized to one. The price is individual-specific since it depends on health insurance coverage. Health insurance status is predetermined. I assume positive but diminishing marginal utilities and marginal products: $U_C > 0, U_{CC} < 0, U_H > 0, U_{HH} < 0, f_M > 0, f_{MM} < 0$.

Medical care utilization can be modelled either as a decision of the individual or as a decision of the physician. I assume that the physician is a perfect agent of the patient, hence I do not consider principal-agent problems. It is an unsettled issue in the literature which is the proper way to model health care demand, see e.g. Jones (2000). If it is assumed that the physician at least partly determines the amount of utilization, then two-step modelling is reasonable. The first stage is the decision of the individual about making an initial contact, the second stage is the (potentially joint) decision of the physician (and the individual) about the amount of utilization. Similar two-stage approach is applied among others by Pohlmeier - Ulrich (1995) and Gurmu (1997).

Since I assume that the physician is a perfect agent, the optimal amount of utilization is the same under

²⁴I neglect any kind of uncertainty in this model. This also implies that health is a deterministic function of initial health status and medical care.

both modelling assumptions. The Lagrangian of the problem is:²⁵

$$\Lambda_i = U(C_i, f(H_{0i}, M_i)) + \lambda_i(Y_i - p_i M_i - C_i).$$

The first order conditions of maximization are (for simplifying the notations I neglect the i index):

$$\begin{aligned} \frac{\partial \Lambda}{\partial C} &= U_C - \lambda = 0 \\ \frac{\partial \Lambda}{\partial M} &= U_H f_M - \lambda p = 0 \\ \frac{\partial \Lambda}{\partial \lambda} &= Y - pM - C = 0. \end{aligned}$$

The determinant of the Hessian is positive, thus the second order condition is satisfied:

$$|H| = \begin{vmatrix} U_{cc} & 0 & -1 \\ 0 & U_{HH} f_M^2 + U_H f_{MM} & -p \\ -1 & -p & 0 \end{vmatrix} = -(U_{HH} f_M^2 + U_H f_{MM}) - p^2 U_{CC} > 0.$$

The Cramer-rule can be applied to find the sign of the partial effect of price on health care demand.

$$\frac{\partial M}{\partial p} = \frac{\begin{vmatrix} U_{cc} & 0 & -1 \\ 0 & \lambda & -p \\ -1 & M & 0 \end{vmatrix}}{|H|} = \frac{-\lambda + Mp U_{CC}}{|H|} < 0.$$

This result shows that if the monotonicity and concavity assumptions are satisfied, the health care demand decreases with medical care price level. It also implies that health insurance coverage which decreases the realized price increases the demand for health care.

If health care utilization is considered as a single decision, an individual decides on no utilization if the optimal level of utilization is negative or zero (corner solution). If two-stage decision making is assumed, the first stage decision is about utilizing the health care or not. This decision is made based on the comparison of utilities with and without health care utilization. If there are no information asymmetries, and physicians are perfect agents of the patients, these two approaches lead to the same health care demand.

Let's assume that the utility function has the following form:

$$U(C_i, H_i) = C_i^a H_i^b$$

This specification is similar to the utility functions used by Cameron et al. (1988). b measures the relative importance of health, and both $a, b \in (0, 1)$. This functional form ensures that utility is increasing but concave in consumption and health, and the marginal utility of consumption increases with health. There is some evidence in the literature that better health is associated with higher marginal utility of consumption, see e.g. Finkelstein et al. (2008). Current-period can be modelled the following way:

$$H_i = H_{0i} (1 + M_i)^{\alpha_i},$$

²⁵This problem, and its solution is similar to the health care demand model of Atherly (2002).

where $\alpha_i \in (0, 1)$.²⁶ Thus, the utility and health production functions satisfy the monotonicity and concavity assumptions used in the above presented more general model. I assume that α_i depends on H_{0i} with $\frac{\partial \alpha_i}{\partial H_{0i}} < 0$. This assumption implies that the same amount of treatment results in less relative improvement in health for healthier people.

The optimal amount of utilization is the solution to the following maximization problem (written up in logarithmic form):

$$\max_{M_i} a \ln(Y_i - p_i M_i) + b \ln[H_{0i}(1 + M_i)^{\alpha_i}].$$

The first-order condition is:

$$-\frac{ap_i}{Y_i - p_i M_i^*} + \frac{b\alpha_i}{1 + M_i^*} = 0.$$

The second-order negativity condition is satisfied. After rearrangements, the optimal level of utilization is:

$$M_i^* = \frac{b\alpha_i \frac{Y_i}{p_i} - a}{b\alpha_i + a}.$$

$\frac{\partial M_i^*}{\partial \alpha_i} > 0$, therefore $\frac{\partial M_i^*}{\partial H_{0i}} < 0$ - the optimal utilization of medical care decreases with initial health. This expression also implies that medical care utilization increases in income and decreases in price. The partial effect of price is larger in absolute value if income is higher. However, this result relies on the assumption that the preference and health production parameters do not depend on income. For example, if the marginal utility of consumption increases with income ($\frac{\partial a}{\partial Y_i} > 0$), then it is possible that $\frac{\partial^2 M_i^*}{\partial p_i \partial Y_i} > 0$. Thus there is no clear theoretical result about the heterogeneity of price effect.

The individual decides on medical care utilization by comparing the expected utility with and without any utilization. The individual chooses not to utilize health care if $M_i^* \leq 0$. This is more likely to happen if the price of medical care is higher or if the initial health status is better, *ceteris paribus*. This model also shows that health care utilization, and the marginal effect of health care price on utilization are sensitive to individual characteristics (preference parameters).

²⁶The deterioration of health is neglected but it could be captured with a multiplier less than one.

B Descriptive statistics and health care financing indicators

B.1 Descriptive statistics

	mean	median	sd		mean	median	sd
age	64.79	64	10.13	smoke=never	0.53	1	0.50
gender	1.54	2	0.50	smoke=stopped	0.28	0	0.45
mstat=with spouse	0.69	1	0.46	smoke=yes	0.19	0	0.39
mstat=with partner	0.04	0	0.20	hosp. bed/th inhabitant	0.56	0.47	0.20
mstat=single	0.27	0	0.44	physicians/th inhabitant	0.37	0.34	0.05
child	0.88	1	0.32	public h./total (%)	73.30	75.70	7.45
net inc (th EUR)	20.94	14.06	72.31	last emp: civil servant	0.11	0	0.32
main residence (th EUR)	91.33	51.54	287.10	last emp: public emp.	0.16	0	0.37
edu=pre primary	0.06	0	0.24	last emp: self-emp.	0.16	0	0.37
edu=primary	0.28	0	0.45	suppl PHI	0.33	0	0.47
edu=lower secondary	0.19	0	0.39	primary PHI	0.05	0	0.22
edu=upper secondary	0.30	0	0.46	# illness	1.35	1	1.45
edu=tertiary	0.18	0	0.38	# ADL problems	0.20	0	0.77
area=big city	0.14	0	0.34	# symptoms	1.45	1	1.62
area=suburbs big city	0.18	0	0.38	firm size not relevant	0.25	0	0.44
area=large town	0.19	0	0.39	firm size 1-5	0.13	0	0.34
area=small town	0.26	0	0.44	firm size 6-15	0.14	0	0.34
area=rural	0.24	0	0.42	firm size 16-24	0.08	0	0.27
emp=retired	0.49	0	0.50	firm size 25-199	0.23	0	0.42
emp=empl., other	0.12	0	0.32	firm size 200-499	0.07	0	0.26
emp=unemp.	0.03	0	0.17	firm size 500-	0.10	0	0.30
emp=disabled	0.03	0	0.17	# gp visits	4.91	3	7.60
emp=homemaker	0.16	0	0.36	# hosp.nights	1.52	0	7.04
emp=civil serv.	0.04	0	0.20	# specialist visits	1.64	0	4.67
emp=self emp.	0.07	0	0.25				
emp=public emp.	0.06	0	0.24				

B.2 Private health insurance coverage and health care utilization - sample means

	Supplementary PHI coverage	Primary PHI coverage	Hospital stay	Visit GP	Visit specialist	# hospital nights (if hosp.>0)	# GP visits (if GP>0)	# specialist visits (if spec.>0)
Au	0.23	0.01	0.19	0.85	0.37	11.59	5.52	3.65
Be	0.76	0.00	0.14	0.92	0.48	9.36	6.18	3.78
Dk	0.36	0.00	0.12	0.81	0.18	8.58	4.01	3.78
Fr	0.83	0.01	0.15	0.93	0.46	8.89	5.74	3.62
Germ	0.13	0.09	0.16	0.92	0.54	12.14	5.40	4.26
Gre	0.05	0.00	0.08	0.76	0.27	8.22	5.43	4.63
It	0.06	0.00	0.12	0.83	0.40	9.73	7.69	4.02
Nl	0.46	0.36	0.09	0.80	0.37	7.74	3.47	3.90
Sp	0.09	0.00	0.11	0.88	0.42	9.13	7.73	4.41
Swe	0.09	0.00	0.11	0.75	0.28	6.66	2.70	3.07
Swi	0.33	0.00	0.12	0.83	0.30	8.93	4.13	3.86

B.3 Health care expenditure by financing agent (% of total, Eurostat 2004)

	General government	Private insurance	Private household out-of-pocket
Au	75.97	5.35	17.40
Be	72.93		
Dk	82.97	1.56	15.41
Fr	79.25	13.19	6.76
Germ	77.38	9.34	12.42
Nl	64.49	19.36	7.90
Sp	70.09	5.87	23.33
Swe	82.26		16.52
Swi	58.52	8.74	31.81

C Adjustment of standard errors in two-step ML estimations

I present here the procedure of calculating standard errors of estimated coefficients when those are estimated with two-step maximum likelihood. This is applicable for the models presented in sections 5.1.2, 5.1.3, and 5.1.4.

I use the formula of asymptotic covariance matrix for two-step ML estimators as presented by Greene (2003), Theorem 17.8. This is based on the results of Murphy - Topel (1985). If the residuals in the first and second step models are uncorrelated, the estimated asymptotic covariance matrix of second-step estimates is:

$$V_2^* = V_2 + V_2(CV_1C')V_2.$$

V_1 and V_2 are the estimated covariance matrices of the first and second step ML estimates (without any adjustment), and

$$C = \frac{1}{n} \sum_{i=1}^n \left(\frac{\partial \ln L_{2i}}{\partial \hat{\chi}_2} \right) \left(\frac{\partial \ln L_{2i}}{\partial \hat{\chi}_1'} \right),$$

where L_{2i} is the contribution of the i th observation to the second step likelihood, $\hat{\chi}_1$ is the vector of first-step parameter estimates, $\hat{\chi}_2$ is the vector of second-step parameter estimates, and n is the number of observations. As a robustness check, I calculated the covariance matrix for the hospital nights estimation without the assumption of independence of first and second step model residuals, both in the 2SRI and hurdle models, but it changed the results only slightly – supporting the statement of Greene (1995) that this simplification is generally reasonable.²⁷

The formula for V_2^* is applied to estimate the covariance matrix of the estimates of equations (3), (7), and (8). V_1 and V_2 are the estimated (not adjusted) variance-covariance matrices of the first and second stage ML estimates. These are obtained based on the observed information matrices (the default in Stata). In the negative binomial regression models the log likelihood functions have the form detailed below under points C.1 and C.2 (to simplify notation, I assume that in both cases the distribution of $\exp(\varepsilon)$ is Gamma($1/a, a$)). The log likelihood with normal heterogeneity is described under point C.3.

C.1 2SRI model

$$\begin{aligned} \ln L_{2ji} &= \ln \left[\Gamma \left(\frac{1}{a} + Y_{ji} \right) \right] - \ln [\Gamma(Y_{ji} + 1)] - \ln \left[\Gamma \left(\frac{1}{a} \right) \right] + \\ &+ \frac{1}{a} \ln \frac{1}{1 + a \exp(X_i \beta_{2j} + \gamma_{2j} PHI_i + \delta_j \hat{u}_i)} + \\ &+ HN_i \ln \frac{a \exp(X_i \beta_{2j} + \gamma_{2j} PHI_i + \delta_j \hat{u}_i)}{1 + a \exp(X_i \beta_{2j} + \gamma_{2j} PHI_i + \delta_j \hat{u}_i)}. \end{aligned}$$

Based on the derivations of Ismail - Jemain (2007), using that $\Gamma(Y_{ji} + 1) = Y_{ji}!$, and $\Gamma\left(\frac{1}{a} + Y_{ji}\right) = \frac{1}{a} \Gamma\left(\frac{1}{a}\right) \prod_{r=1}^{Y_{ji}-1} \left(\frac{1}{a} + r\right)$,

²⁷The formula without simplification is $V_2^* = V_2 + V_2(CV_1C' - RV_1C' - CV_1R')V_2$, where $R = \frac{1}{n} \sum_{i=1}^n \left(\frac{\partial \ln L_{2i}}{\partial \hat{\chi}_2} \right) \left(\frac{\partial \ln L_{1i}}{\partial \hat{\chi}_1} \right)$, L_{1i} being the contribution of the i th observation to the first step likelihood.

the log likelihood can be rewritten²⁸:

$$\begin{aligned} \ln L_{2ji} &= \sum_{r=1}^{Y_{ji}-1} \ln(1+ar) - Y_{ji} \ln(a) - \ln(Y_{ji}!) + Y_{ji} \ln [a \exp(X_i \beta_{2j} + \gamma_{2j} P H I_i + \delta_j \hat{u}_i)] - \\ &\quad - \left(\frac{1}{a} + Y_{ji} \right) \ln [1 + a \exp(X_i \beta_{2j} + \gamma_{2j} P H I_i + \delta_j \hat{u}_i)]. \end{aligned}$$

The first derivatives are:²⁹

$$\frac{\partial \ln L_{2ji}}{\partial \hat{\chi}_2} = \begin{bmatrix} \frac{Y_{ji} - \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)}{1 + \hat{a} \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)} \begin{bmatrix} X'_i \\ P H I_i \\ \hat{u}_i \end{bmatrix} \\ \sum_{r=1}^{Y_{ji}-1} \frac{r}{1+\hat{a}r} + \frac{1}{\hat{a}^2} \ln [1 + \hat{a} \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)] - \\ - \left(\frac{1}{\hat{a}} + Y_{ji} \right) \frac{\exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)}{1 + \hat{a} \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)} \end{bmatrix},$$

$$\begin{aligned} \frac{\partial \ln L_{2ji}}{\partial \hat{\chi}_1} &= \hat{\delta}_j \left[Y_{ji} - \left(\frac{1}{\hat{a}} + Y_{ji} \right) \frac{\hat{a} \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)}{1 + \hat{a} \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)} \right] \frac{\partial (P H I_i - \Phi(Z_i \hat{\alpha}))}{\partial \hat{\alpha}} = \\ &= \hat{\delta}_j \left[Y_{ji} - \left(\frac{1}{\hat{a}} + Y_{ji} \right) \frac{\hat{a} \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)}{1 + \hat{a} \exp(X_i \hat{\beta}_{2j} + \hat{\gamma}_{2j} P H I_i + \hat{\delta}_j \hat{u}_i)} \right] \cdot [-\phi(Z_i \hat{\alpha})] Z'_i. \end{aligned}$$

C.2 Hurdle model

$$\begin{aligned} \ln L_{2ji} &= \ln \left[\Gamma \left(\frac{1}{a} + Y_{ji} \right) \right] - \ln [\Gamma(Y_{ji} + 1)] - \ln \left[\Gamma \left(\frac{1}{a} \right) \right] + \\ &\quad + \frac{1}{a} \ln \frac{1}{1 + a \exp(\tilde{X}_i \beta_{4j} + \gamma_{4j} P H I_i + \varphi_j M_{-Y_{ji}})} + \\ &\quad + Y_{ji} \ln \frac{a \exp(\tilde{X}_i \beta_{4j} + \gamma_{4j} P H I_i + \varphi_j M_{-Y_{ji}})}{1 + a \exp(\tilde{X}_i \beta_{4j} + \gamma_{4j} P H I_i + \varphi_j M_{-Y_{ji}})}. \end{aligned}$$

Using the properties of gamma function:

$$\begin{aligned} \ln L_{2ji} &= \sum_{r=1}^{Y_{ji}-1} \ln(1+ar) - Y_{ji} \ln(a) - \ln(Y_{ji}!) + Y_{ji} \ln [a \exp(\tilde{X}_i \beta_{4j} + \gamma_{4j} P H I_i + \varphi_j M_{-Y_{ji}})] - \\ &\quad - \left(\frac{1}{a} + Y_{ji} \right) \ln [1 + a \exp(\tilde{X}_i \beta_{4j} + \gamma_{4j} P H I_i + \varphi_j M_{-Y_{ji}})]. \end{aligned}$$

²⁸The applied properties of gamma distribution function are described also in Abramowitz - Stegun (1972).

²⁹The negative binomial regression in Stata estimates the coefficient and variance-covariance matrix for $\ln a$, therefore in calculating the correct standard errors I also treat $\ln a$ as the estimated parameter, and use that $\frac{\partial \ln L_{2ji}}{\partial \ln a} = a \frac{\partial \ln L_{2ji}}{\partial a}$.

Now the first derivatives are:

$$\frac{\partial \ln L_{2ji}}{\partial \tilde{\chi}_2} = \begin{bmatrix} \frac{Y_{ji} - \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})}{1 + \hat{a} \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})} \begin{bmatrix} \tilde{X}'_i \\ PHI_i \\ M_{-Y_{ji}} \end{bmatrix} \\ \sum_{r=1}^{Y_{ji}-1} \frac{r}{1+\hat{a}r} + \frac{1}{\hat{a}^2} \ln \left[1 + \hat{a} \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}}) \right] - \\ - \left(\frac{1}{\hat{a}} + Y_{ji} \right) \frac{\exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})}{1 + \hat{a} \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})} \end{bmatrix},$$

$$\frac{\partial \ln L_{2ji}}{\partial \tilde{\chi}_1} = \hat{\varphi}_j \left[Y_{ji} - \left(\frac{1}{\hat{a}} + Y_{ji} \right) \frac{\hat{a} \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})}{1 + \hat{a} \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})} \right] \frac{\partial \left(\frac{\phi(X_i \hat{\beta}_{3j} + \hat{\gamma}_{3j} PHI_i)}{\Phi(X_i \hat{\beta}_{3j} + \hat{\gamma}_{3j} PHI_i)} \right)}{\partial \tilde{\chi}_1} =$$

$$= \hat{\varphi}_j \left[Y_{ji} - \left(\frac{1}{\hat{a}} + Y_{ji} \right) \frac{\hat{a} \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})}{1 + \hat{a} \exp(\tilde{X}_i \hat{\beta}_{4j} + \hat{\gamma}_{4j} PHI_i + \hat{\varphi}_j M_{-Y_{ji}})} \right] \cdot$$

$$\cdot \left[-(\tilde{X}_i \hat{\beta}_{3j} + \hat{\gamma}_{3j} PHI_i) M_{-Y_{ji}} - M_{-Y_{ji}}^2 \right] \begin{bmatrix} X'_i \\ PHI_i \end{bmatrix}.$$

C.3 LIML model

$$L_{2ji} = \frac{1}{K} \sum_{k=1}^K \frac{\exp(-\exp(\tilde{X}_i \beta_{5j} + \gamma_{5j} PHI_i + \sigma_j u_{ji}^k)) \exp(\tilde{X}_i \beta_{5j} + \gamma_{5j} PHI_i + \sigma_j u_{ji}^k)^{Y_{ji}}}{Y_{ji}!} \cdot$$

$$\cdot \left[1 - \Phi \left(\frac{-Z_i \hat{\alpha} - u_{ji}^k c_{13}}{\sqrt{1 - c_{13}^2}} \right) - \Phi \left(\frac{-\tilde{X}_i \hat{\beta}_{3j} - \hat{\gamma}_{3j} PHI_i - u_{ji}^k c_{23}}{\sqrt{1 - c_{23}^2}} \right) + \right.$$

$$\left. + BINORM \left(\frac{-Z_i \hat{\alpha} - u_{ji}^k c_{13}}{\sqrt{1 - c_{13}^2}}, \frac{-\tilde{X}_i \hat{\beta}_{3j} - \hat{\gamma}_{3j} PHI_i - u_{ji}^k c_{23}}{\sqrt{1 - c_{23}^2}}, \frac{\hat{c}_{12} - c_{13} c_{23}}{\sqrt{1 - c_{13}^2} \sqrt{1 - c_{23}^2}} \right) \right]^{PHI_i} \cdot$$

$$\cdot \left[\Phi \left(\frac{-Z_i \hat{\alpha} - u_{ji}^k c_{13}}{\sqrt{1 - c_{13}^2}} \right) - BINORM \left(\frac{-Z_i \hat{\alpha} - u_{ji}^k c_{13}}{\sqrt{1 - c_{13}^2}}, \frac{-\tilde{X}_i \hat{\beta}_{3j} - \hat{\gamma}_{3j} PHI_i - u_{ji}^k c_{23}}{\sqrt{1 - c_{23}^2}}, \frac{\hat{c}_{12} - c_{13} c_{23}}{\sqrt{1 - c_{13}^2} \sqrt{1 - c_{23}^2}} \right) \right]^{1 - PHI_i},$$

where u_{ji}^k is the k th quasi-random draw from the standard normal distribution for individual i and dependent variable Y_j , σ_j^2 is the variance of ε_{5ji} , \hat{c}_{12} is the estimated correlation between ν and ε_3 , $c_{13} = corr(\nu, \varepsilon_3)$, $c_{23} = corr(\varepsilon_3, \varepsilon_5)$. *BINORM* stands for the bivariate normal cumulative distribution function for standard normal variables, and with the correlation as the third argument.

The components of the $\frac{\partial \ln L_{2ji}}{\partial \tilde{\chi}_2}$ matrix are obtained through differentiating $\ln L_{2ji}$ with respect to $\hat{\beta}_{5j}$, $\hat{\sigma}_j$, \hat{c}_{13} , and \hat{c}_{23} . $\frac{\partial \ln L_{2ji}}{\partial \tilde{\chi}_1}$ is obtained through differentiating $\ln L_{2ji}$ with respect to $\hat{\alpha}$, $\hat{\beta}_{3j}$, $\hat{\gamma}_{3j}$ and \hat{c}_{12} . I apply numerical differentiation in calculating the partial derivatives of the bivariate normal distribution function.

D Estimation results

D.1 Benchmark model

	Suppl PHI	nr. hosp.nights	nr. GP visits	nr. spec.visits		Suppl PHI	nr. hosp.nights	nr. GP visits	nr. spec.visits
age	-0.013***	0.026***	0.008***	-0.013***	main phi Ge	0.076	-0.214***		-0.103
female	0.019	-0.104	0.062***	0.147***	main phi NI	-0.172	0.02		-0.205**
mstat=with partner	0.137***	0.318**	0.042	0.134**	heart problems	0.631***	0.274***		0.448***
mstat=single	0.066**	0.108	0.096***	-0.006	high blood pressure	0.156**	0.282***		0.081***
child	0.157***	0.226**	0.01	0.061	high blood cholesterol	-0.241***	0.048***		0.04
log inc	0.079***				stroke	0.620***	0.163***		0.206***
log net inc: Au		0.032	-0.017*	-0.028*	diabetes	0.412***	0.320***		0.355***
log net inc: Ge		-0.083***	-0.026***	0.018	lung disease	0.501***	0.172***		0.212***
log net inc: Swe		-0.056	-0.032	0.032	asthma	0.045	0.169***		0.01
log net inc: NI		0.114	0.053***	0.123***	arthritis or rheumatism	0.158*	0.128***		0.234***
log net inc: Sp		0.193*	0.059***	0.089**	osteoporosis	0.12	0.095***		0.257***
log net inc: It		-0.045	0.030**	0.055*	cancer	1.200***	0.215***		0.923***
log net inc: Fr		-0.120***	-0.006	0.018	stomach ulcer	0.387***	0.051**		0.067
log net inc: DK		-0.112	0.001	-0.017	parkinson disease	-0.657**	-0.001		0.167
log net inc: Gre		0.06	0.034*	0.073**	cataracts	0.063	-0.056**		0.238***
log net inc: Swi		0.194**	0.078***	0.083**	hip or femoral fracture	0.731***	0.120***		0.102
log net inc: Be		-0.107*	0.019*	0.029	difficulties dressing	0.158	0.125***		0.121**
log home	0.017***				difficulties walking across a room	0.432	-0.052		0.089
log home: Au		-0.021	-0.006	0.005	difficulties bathing or showering	0.388**	0.125***		0.031
log home: Ge		0.029	0.007	0.001	difficulties eating, cutting up food	-0.053	0.032		-0.015
log home: Swe		-0.038	0.009	0.007	difficulties getting in or out of bed	-0.184	0.083**		0.097
log home: NI		0.007	0.002	-0.005	difficulties using the toilet	0.186	-0.071		-0.051
log home: Sp		0.005	0.011	0.003	bothered by pain in a joint	0.119*	0.142***		0.248***
log home: It		0.066**	-0.005	-0.003	bothered by heart trouble	0.652***	0.156***		0.230***
log home: Fr		0.003	0	0.016	bothered by breathlessness	0.298***	0.076***		0.086*
log home: Dk		0.059*	0.003	0.015	bothered by persistent cough	-0.184	0.098***		0.222***
log home: Gre		0.032	0.009	-0.02	bothered by swollen legs	0.048	0.085***		0.088**
log home: Swi		0.024	0.003	0.016	bothered by sleeping problems	0.12	0.154***		0.226***
log home: Be		0.001	0.003	-0.003	bothered by falling down	0.13	-0.02		0.07
edu=primary	-0.230***	-0.213	-0.036	0.038	bothered by fear of falling down	0.052	0.016		0.148***
edu=lower secondary	-0.141***	-0.134	-0.049	0.157**	bothered by dizziness	0.243**	0.163***		0.189***
edu=upper secondary	-0.345***	-0.118	-0.094***	0.300***	bothered by intestine problems	0.358***	0.141***		0.284***
edu=tertiary	-0.228***	-0.295*	-0.121***	0.373***	bothered by incontinence	0.118	0.025		0.178***
last job=civil servant	0.182***				firm size 1-5	0.128***			
last job=self emp.	0.146***				firm size 6-15	0.095**			
last job=public emp.	-0.02				firm size 16-24	-0.095**			
emp=empl., other	-0.390***	-0.139***	-0.284***		firm size 25-199	0.141***			
emp=unempl.	-0.099	0.021	-0.042		firm size 200-499	0.187***			
emp=disabled	0.882***	0.433***	0.516***		firm size 500-	0.348***			
emp=homemaker	-0.07	0.028	-0.047		partner's firm size 1-5	0.071*			
emp=civil servant	0.197	0.015	-0.182***		partner's firm size 6-15	0.056			
emp=self emp.	-0.416***	-0.309***	-0.335***		partner's firm size 16-24	-0.066			
emp=public emp.	-0.433***	-0.05	-0.163***		partner's firm size 25-199	0.091***			
area=suburbs big city	0.267***	0.092	-0.104**		partner's firm size 200-499	0.149***			
area=large town	0.024	0.156	-0.214***		partner's firm size 500-	0.273***			
area=small town	0.059*	0.236**	-0.249***		partner's last job=civil servant	0.149***			
area=rural	0.006	0.211*	-0.238***		partner's last job=self emp.	0.080**			
smoke=stopped	0.306**	0.021	0.131***		partner's last job=public emp.	-0.073**			
smoke=yes	0.02	-0.064***	-0.147***		South countries	-0.703	0.558***	0.526	
nr. physicians	-2.859***	12.921	0.755	0.315	Partner physician visits		0.120***	0.321***	
nr. hosp.beds	2.110***	3.048	1.832***	2.331***	Constant	-0.409*	-19.911***	-4.016***	-3.738
public total	-0.007***	0.146***	0.040***	0.029	Observations	24756	24643	24651	24712
suppl phi	0.159*	-0.001	0.093**						

* significant at 10%; ** significant at 5%; *** significant at 1%

D.2 Two-stage residual inclusion model

	nr. hosp.nights	nr. GP visits	nr. spec.visits		nr. hosp.nights	nr. GP visits	nr. spec.visits
age	0.030***	0.006***	-0.010***	nr. physicians	12.964	0.579	0.586
female	-0.112	0.064***	0.142***	nr. hosp.beds	2.55	1.988***	1.985**
mstat=with partner	0.274*	0.056*	0.102	public total	0.148***	0.041***	0.029
mstat=single	0.113	0.100***	-0.008	suppl phi	1.283**	-0.306**	0.727***
child	0.175*	0.024	0.03	main phi Ge	0.055	-0.200***	-0.13
log net inc: Au	-0.002	-0.008	-0.044**	main phi NI	-0.191	0.027	-0.223**
log net inc: Ge	-0.088***	-0.025***	0.016	heart problems	0.634***	0.274***	0.447***
log net inc: Swe	-0.044	-0.034	0.036	high blood pressure	0.154**	0.283***	0.080***
log net inc: NI	0.125	0.052***	0.126***	high blood cholesterol	-0.245***	0.048***	0.041
log net inc: Sp	0.205**	0.056***	0.094***	stroke	0.627***	0.161***	0.208***
log net inc: It	-0.031	0.027*	0.060**	diabetes	0.418***	0.319***	0.358***
log net inc: Fr	-0.122***	-0.005	0.017	lung disease	0.503***	0.171***	0.210***
log net inc: Dk	-0.106	-0.002	-0.014	asthma	0.043	0.169***	0.011
log net inc: Gre	0.082	0.032*	0.080**	arthritis or rheumatism	0.161*	0.128***	0.232***
log net inc: Swi	0.201**	0.078***	0.084**	osteoporosis	0.118	0.095***	0.257***
log net inc: Be	-0.101*	0.019*	0.03	cancer	1.192***	0.216***	0.922***
log home: Au	-0.03	-0.003	0	stomach ulcer	0.391***	0.051**	0.068
log home: Ge	0.031	0.007	0	parkinson disease	-0.639*	-0.003	0.171
log home: Swe	-0.033	0.008	0.009	cataracts	0.052	-0.056**	0.236***
log home: NI	0.01	0.002	-0.004	hip or femoral fracture	0.735***	0.121***	0.102
log home: Sp	0.008	0.01	0.006	difficulties dressing	0.163	0.125***	0.122**
log home: It	0.069**	-0.006	-0.001	difficulties walking across a room	0.438*	-0.05	0.084
log home: Fr	0.002	0	-0.016	difficulties bathing or showering	0.378**	0.125***	0.032
log home: Dk	0.062*	0.002	0.015	difficulties eating, cutting up food	-0.059	0.032	-0.014
log home: Gre	0.035	0.008	-0.018	difficulties getting in or out of bed	-0.186	0.082*	0.103
log home: Swi	0.027	0.002	0.017	difficulties using the toilet	0.193	-0.072	-0.057
log home: Be	0.001	0.003	-0.004	bothered by pain in a joint	0.115*	0.142***	0.247***
edu=primary	-0.13	-0.057**	0.082	bothered by heart trouble	0.653***	0.157***	0.233***
edu=lower secondary	-0.084	-0.060**	0.179***	bothered by breathlessness	0.307***	0.075***	0.087*
edu=upper secondary	-0.002	-0.124***	0.364***	bothered by persistent cough	-0.195	0.098***	0.222***
edu=tertiary	-0.224	-0.137***	0.406***	bothered by swollen legs	0.054	0.084***	0.087**
emp=empl., other	-0.376***	-0.143***	-0.277***	bothered by sleeping problems	0.12	0.155***	0.226***
emp=unempl.	-0.084	0.019	-0.036	bothered by falling down	0.134	-0.019	0.067
emp=disabled	0.895***	0.429***	0.522***	bothered by fear of falling down	0.051	0.016	0.151***
emp=homemaker	-0.039	0.02	-0.028	bothered by dizziness	0.236**	0.163***	0.191***
emp=civil servant	0.117	0.031	-0.217***	bothered by intestine problems	0.362***	0.141***	0.283***
emp=self emp.	-0.404***	-0.310***	-0.331***	bothered by incontinence	0.119	0.026	0.178***
emp=public emp.	-0.412***	-0.055*	-0.152**	South countries	-0.69	0.569***	0.513
area=suburbs big city	-0.009	0.045*	-0.162***	Partner physician visits		0.128***	0.310***
area=large town	0.153	-0.024	-0.219***	PHI residual	-1.133*	0.307**	-0.639**
area=small town	0.223**	-0.014	-0.258***	Constant	-20.160***	-3.945***	-3.874*
area=rural	0.211*	-0.025	-0.236***	Observations	24643	24651	24712
smoke=stopped	0.309***	0.022	0.132***				
smoke=yes	0.02	-0.064***	-0.147***				

* significant at 10%; ** significant at 5%; *** significant at 1%

D.3 Hurdle model

D.3.1 First stage decision

	Nonzero hosp.nights (probit)	Nonzero GP visits (probit)	Nonzero spec.visits (probit)		Nonzero hosp.nights (probit)	Nonzero GP visits (probit)	Nonzero spec.visits (probit)
age	0.004***	0.005***	-0.007***	nr. physicians	0.954	-4.006	0.751
female	-0.04	0.137***	0.179***	nr. hosp.beds	1.576*	1.929***	0.402
mstat=with partner	0.107*	-0.011	-0.03	public total	0.042**	-0.01	0.023
mstat=single	0.004	0.062**	-0.036	suppl phi	0.1	0.063	0.099*
child	0.096***	0.048	0.036	main phi Ge	0.092	-0.11	-0.03
log net inc: Au	0.009	-0.024	0.031**	main phi NI	-0.113	0.152**	-0.066
log net inc: Ge	-0.043***	0.022**	0.017**	heart problems	0.328***	0.399***	0.461***
log net inc: Swe	0	0.044	-0.048	high blood pressure	0.068***	0.474***	0.087***
log net inc: NI	0.047	0.034	0.033	high blood cholesterol	-0.038	0.263***	0.050**
log net inc: Sp	0.033	0.052*	0.01	stroke	0.312***	0.047	0.119**
log net inc: It	-0.023	0.064***	-0.011	diabetes	0.186***	0.464***	0.200***
log net inc: Fr	-0.043***	0.052***	0.009	lung disease	0.171***	0.304***	0.131***
log net inc: Dk	-0.01	0.045	-0.082***	asthma	0.043	0.151**	0.034
log net inc: Gre	0.016	0.024	-0.009	arthritis or rheumatism	0.022	0.243***	0.179***
log net inc: Swi	0.073**	0.046*	0.036	osteoporosis	0.004	0.306***	0.269***
log net inc: Be	-0.033*	0.052***	0.01	cancer	0.545***	0.410***	0.679***
log home: Au	-0.006	-0.004	-0.009	stomach ulcer	0.103**	0.011	0.135***
log home: Ge	0.005	0.006	0.017**	parkinson disease	-0.132	-0.260*	0.491***
log home: Swe	0.001	0.015	0.025***	cataracts	0.097**	0.026	0.181***
log home: NI	0.001	0.008	0.005	hip or femoral fracture	0.395***	-0.068	0.008
log home: Sp	-0.011	0.012	0.017*	difficulties dressing	0.132***	-0.038	0.074*
log home: It	0.011	0.007	0.015*	difficulties walking across a room	0.155*	-0.013	-0.145*
log home: Fr	0.002	0.002	-0.002	difficulties bathing or showering	0.179**	0.015	-0.059
log home: Dk	0.002	0.006	0.016	difficulties eating, cutting up food	0.018	0.013	0.009
log home: Gre	0.01	0.019*	0.006	difficulties getting in or out of bed	-0.132*	0.133	-0.034
log home: Swi	0.002	-0.003	0.004	difficulties using the toilet	-0.02	-0.218*	-0.159*
log home: Be	0.007	0.009	0.015**	bothered by pain in a joint	0.043*	0.222***	0.163***
edu=primary	0.026	0.099*	0.035	bothered by heart trouble	0.290***	0.158**	0.132***
edu=lower secondary	0.034	0.126**	0.186***	bothered by breathlessness	0.080**	0.131***	0.038
edu=upper secondary	0.041	0.147**	0.257***	bothered by persistent cough	-0.02	0.183***	0.056
edu=tertiary	0.02	0.139**	0.323***	bothered by swollen legs	0.024	0.049	-0.01
emp=empl., other	-0.140***	-0.041	-0.115***	bothered by sleeping problems	0.081***	0.115***	0.105***
emp=unempl.	-0.078	-0.032	-0.133**	bothered by falling down	0.184***	0.026	0.109**
emp=disabled	0.350***	0.187**	0.303***	bothered by fear of falling down	-0.038	0.089	0.072**
emp=homemaker	0.004	-0.055	-0.038	bothered by dizziness	0.154***	0.232***	0.086***
emp=civil servant	-0.019	0.109*	-0.121**	bothered by intestine problems	0.153***	0.274***	0.194***
emp=self emp.	-0.112**	-0.167***	-0.192***	bothered by incontinence	0.029	0.144**	0.116***
emp=public emp.	-0.061	-0.041	-0.065	South countries	0.269	0.3	0.249
area=suburbs big city	0.021	0.014	-0.023	Partner physician visits		0.257***	0.352***
area=large town	0.046	-0.019	-0.136***	Constant	-6.365***	0.8	-3.268**
area=small town	0.074*	-0.078**	-0.164***	Observations	24756	24756	24756
area=rural	0.042	-0.104***	-0.141***				
smoke=stopped	0.103***	0.028	0.101***				
smoke=yes	-0.002	-0.201***	-0.111***				

* significant at 10%; ** significant at 5%; *** significant at 1%

D.3.2 Second stage decision

	nr. hosp.nights	nr. GP visits	nr. spec.visits		nr. hosp.nights	nr. GP visits	nr. spec.visits
age	0.006**	0.006***	-0.007***	nr. physicians	6.55	2.647*	-1.377
female	0.014	0	-0.060**	nr. hosp.beds	1.429	1.216***	1.598**
mstat=with partner	-0.091	0.054*	0.126***	public total	0.024	0.043***	-0.006
mstat=single	0.089**	0.051***	0.016	suppl phi	-0.148***	-0.032**	0.016
child	-0.140**	-0.016	0.035	main phi Ge	-0.197	-0.189***	-0.058
log net inc: Au	0.019	-0.012	-0.042***	main phi NI	0.285*	-0.038	-0.124*
log net inc: Ge	0.007	-0.029***	0.009	heart problems	-0.225*	0.166***	0.044
log net inc: Swe	0.037	-0.040*	0.075**	high blood pressure	-0.051	0.133***	-0.007
log net inc: NI	0.058	0.043***	0.065***	high blood cholesterol	-0.144***	-0.027**	-0.026
log net inc: Sp	0.058	0.040***	0.045*	stroke	-0.138	0.138***	0.084**
log net inc: It	0	0.004	0.046**	diabetes	-0.086	0.191***	0.148***
log net inc: Fr	-0.013	-0.018***	0.013	lung disease	0.021	0.095***	0.096***
log net inc: Dk	0.024	-0.009	0.065**	asthma	-0.004	0.106***	-0.065
log net inc: Gre	0.005	0.024	0.060**	arthritis or rheumatism	0.057	0.067***	0.055**
log net inc: Swi	0.037	0.062***	0.03	osteoporosis	0.012	0.029	0.064**
log net inc: Be	-0.009	0.001	0.017	cancer	-0.246	0.099***	0.370***
log home: Au	-0.008	-0.004	0.014**	stomach ulcer	0.023	0.044**	-0.005
log home: Ge	0.005	0.004	-0.016**	parkinson disease	-0.004	-0.011	-0.191**
log home: Swe	-0.004	0.004	-0.020**	cataracts	-0.189***	-0.063***	0.052
log home: NI	0.001	0.001	-0.013	hip or femoral fracture	-0.119	0.100***	0.055
log home: Sp	0.031*	0.007	-0.018*	difficulties dressing	-0.141*	0.135***	0.067*
log home: It	0.019	-0.006	-0.020**	difficulties walking across a room	0.061	-0.04	0.113
log home: Fr	0.008	-0.002	-0.018**	difficulties bathing or showering	0.013	0.140***	0.116***
log home: Dk	0.044***	0.003	0.001	difficulties eating, cutting up food	0.046	0.003	-0.039
log home: Gre	-0.009	-0.001	-0.029***	difficulties getting in or out of bed	0.139	0.052	0.135**
log home: Swi	0.028	0.004	0.01	difficulties using the toilet	0.025	-0.011	0.056
log home: Be	-0.011	0	-0.015*	bothered by pain in a joint	-0.047	0.050***	0.052**
edu=primary	-0.131*	-0.058**	0.070*	bothered by heart trouble	-0.088	0.141***	0.104***
edu=lower secondary	-0.123	-0.080***	0.037	bothered by breathlessness	0.017	0.060***	0.071**
edu=upper secondary	-0.163**	-0.136***	0.104**	bothered by persistent cough	0.003	0.047**	0.085**
edu=tertiary	-0.199**	-0.165***	0.115**	bothered by swollen legs	0.016	0.074***	0.047*
emp=empl., other	-0.071	-0.119***	-0.159***	bothered by sleeping problems	-0.047	0.119***	0.135***
emp=unempl.	0.191	0.027	0.051	bothered by falling down	-0.213**	-0.02	-0.045
emp=disabled	-0.073	0.347***	0.288***	bothered by fear of falling down	0.027	0.021	0.085***
emp=homemaker	-0.001	0.053***	0.029	bothered by dizziness	-0.126*	0.109***	0.085***
emp=civil servant	0.148	-0.024	0.005	bothered by intestine problems	-0.042	0.072***	0.099***
emp=self emp.	-0.157	-0.203***	-0.111**	bothered by incontinence	0.042	-0.007	0.054
emp=public emp.	-0.275***	-0.012	-0.049	South countries	-0.008	0.477***	0.446
area=suburbs big city		0.016	-0.076**	Inv. Mills	-1.133**	-0.489***	-0.074
area=large town		-0.014	-0.099***	Constant	-1.362	-3.675***	1.653
area=small town		0.014	-0.106***	Observations	3040	20946	9570
area=rural		0.02	-0.119***				
smoke=stopped	0.053	-0.002	0				
smoke=yes	0.052	0.022	-0.046*				

* significant at 10%; ** significant at 5%; *** significant at 1%

D.4 LIML model

	nr. hosp.nights	nr. GP visits	nr. spec.visits		nr. hosp.nights	nr. GP visits	nr. spec.visits
age	0.000	0.001	-0.007***	nr. physicians	9.171	1.962	-0.894
female	0.030	-0.017	-0.105***	nr. hosp.beds	1.739	0.265	0.369
mstat=with partner	-0.093	0.078**	0.129*	public total	0.044	0.025**	-0.008
mstat=single	0.069*	0.038**	0.092***	suppl phi	0.338**	-0.415***	-0.161
child	-0.035	0.018	0.072*	main phi Ge	-0.228*	-0.008	0.077
log net inc: Au	0.017	0.001	-0.026*	main phi NI	0.115	-0.142**	-0.092
log net inc: Ge	-0.025*	-0.012	0.008	heart problems	0.005	0.124***	-0.059
log net inc: Swe	0.055	-0.074**	0.017	high blood pressure	-0.016	0.029**	-0.038
log net inc: NI	0.078	-0.013	0.017	high blood cholesterol	-0.103***	-0.038**	-0.023
log net inc: Sp	0.114**	0.041**	-0.004	stroke	0.061	0.114***	0.058
log net inc: It	0.011	0.004	0.017	diabetes	-0.003	0.084***	0.014
log net inc: Fr	-0.020	-0.025***	0.014	lung disease	0.127**	0.072***	0.037
log net inc: Dk	0.031	-0.034	0.049	asthma	0.008	0.077***	-0.090*
log net inc: Gre	-0.004	0.013	0.018	arthritis or rheumatism	0.029	0.034**	-0.025
log net inc: Swi	0.096*	0.032	0.031	osteoporosis	-0.053	0.011	0.010
log net inc: Be	-0.051*	-0.017	0.005	cancer	0.036	0.092***	0.045
log home: Au	-0.008	0.004	0.012	stomach ulcer	0.065	0.038	-0.013
log home: Ge	0.007	0.001	-0.009	parkinson disease	-0.126	0.031	-0.381***
log home: Swe	-0.016	-0.011	-0.009	cataracts	-0.017	-0.032	-0.073*
log home: NI	-0.002	0.000	-0.010	hip or femoral fracture	0.077	0.091**	-0.033
log home: Sp	0.017	-0.009	-0.011	difficulties dressing	-0.056	0.076***	-0.010
log home: It	0.007	-0.006	-0.028**	difficulties walking across a room	0.186**	0.009	0.246***
log home: Fr	-0.007	-0.007	-0.019	difficulties bathing or showering	0.113**	0.114***	0.093*
log home: Dk	0.042***	-0.008	-0.013	difficulties eating, cutting up food	0.064	0.018	0.060
log home: Gre	-0.001	-0.013*	-0.016	difficulties getting in or out of bed	0.049	0.047	0.053
log home: Swi	-0.014	-0.005	-0.010	difficulties using the toilet	-0.083	-0.053	0.052
log home: Be	0.005	0.000	-0.010	bothered by pain in a joint	-0.038	0.031**	-0.048
edu=primary	-0.038	-0.084***	0.028	bothered by heart trouble	0.090**	0.105***	0.001
edu=lower secondary	-0.052	-0.110***	-0.059	bothered by breathlessness	0.043	0.047**	0.021
edu=upper secondary	-0.057	-0.154***	-0.001	bothered by persistent cough	0.023	0.009	0.049
edu=tertiary	-0.093	-0.133***	0.019	bothered by swollen legs	0.058	0.043**	0.024
emp=empl., other	-0.140*	-0.097***	0.049	bothered by sleeping problems	0.036	0.087***	0.080***
emp=unempl.	0.062	0.032	0.136	bothered by falling down	-0.051	0.034	-0.042
emp=disabled	0.088	0.206***	0.133**	bothered by fear of falling down	-0.031	-0.004	0.074*
emp=homemaker	0.011	0.053***	0.097**	bothered by dizziness	-0.015	0.094***	-0.002
emp=civil servant	0.113	0.056	0.040	bothered by intestine problems	0.076**	0.008	-0.024
emp=self emp.	-0.220**	-0.188***	0.065	bothered by incontinence	0.033	-0.021	0.037
emp=public emp.	-0.212**	-0.010	0.054	South countries	-0.159	-0.044	0.215
area=suburbs big city		0.061**	-0.046	Constant	-5.521	-0.526	3.575
area=large town		-0.021	-0.118***	Observations	3040	20946	9570
area=small town		0.006	-0.026				
area=rural		-0.001	-0.048				
smoke=stopped	0.122***	-0.013	-0.043				
smoke=yes	0.070	0.038*	0.006				

* significant at 10%; ** significant at 5%; *** significant at 1%

References

- Abramowitz, M., and I. A. Stegun, eds. 1972. *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*. National Bureau of Standards, 10th edition.
- Arabmazar, A., and P. Schmidt. 1982. "An Investigation of the Robustness of the Tobit Estimator to Non-Normality." *Econometrica*, 50(4): 1055-1063.
- Atherly, A. 2002. "The Effect of Medicare Supplemental Insurance on Medicare Expenditures." *International Journal of Health Care Finance and Economics*, 2: 137-162.
- Bago d'Uva, T., and A. M. Jones. 2009. "Health care utilisation in Europe: New evidence from the EHCP." *Journal of Health Economics*, 28: 265-279.
- Bolin, K. et al. 2009. "Utilisation of physician services in the 50+ population: the relative importance of individual versus institutional factors in 10 European countries." *International Journal of Health Care Finance and Economics*, 9(1): 83-112.
- Cameron, A. C. et al. 1988. "A Microeconomic Model of the Demand for Health Care and Health Insurance in Australia." *The Review of Economic Studies*, 55(1): 85-106.
- Cameron, A. C., and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. Cambridge University Press.
- Cappellari, L., and S. P. Jenkins. (2006a) "Calculation of Multivariate Normal Probabilities by Simulation, with Applications to Maximum Simulated Likelihood Estimation." *IZA Discussion Paper*, No. 2112.
- Cappellari, L., and S. P. Jenkins. (2006b) *MVPROBIT: Stata module to calculate multivariate probit regression using simulated maximum likelihood*.
- Cavaco, S., J.-M. Etienne, and A. Skalli. 2007. "Identifying causal paths between health and socio-economic status: Evidence from European older workforce surveys." *University of Aarhus Working Paper*, No. 07-8.
- Davis, M. A. 2006. *The Insurance, Health, and Savings Decisions of Elderly Women Living Alone*. Dissertation, unpublished.
- Deb, P., and P. K. Trivedi. 1997. "Demand for Medical Care by the Elderly: A Finite Mixture Approach." *Journal of Applied Econometrics*, 12: 313-336.
- Deb, P., and P. K. Trivedi. 2006. "Maximum simulated likelihood estimation of a negative binomial regression model with multinomial endogenous treatment." *The Stata Journal*, 6(2): 246-255.
- De Nardi, M., E. French, and J. B. Jones. 2006. "Differential Mortality, Uncertain Medical Expenses, and the Saving of Elderly Singles." *NBER Working Paper*, No. 12554.
- Feldstein, M. S. 1973. "The Welfare Loss of Excess Health Insurance." *The Journal of Political Economy*, 81(2): 251-280.
- Finkelstein, A., E. F. P. Luttmer, and M. J. Notowidigdo. 2008. "What Good is Wealth Without Health? The Effect of Health on the Marginal Utility of Consumption." *NBER Working Paper*, No. 14089.

- Gerdtham, U-G. et al. 1992. "An econometric analysis of health care expenditure: A cross-section study of the OECD countries." *Journal of Health Economics*, 11: 63-84.
- Gerdtham, U-G., and B. J. Jönsson. 2000. "International Comparisons of Health Expenditure: Theory, Data and Econometric Analysis." in *Handbook of Health Economics*, 2000, vol. 1, Chapter 1, pp. 11-53.
- Gibbons, R. D., and V. Wilcox-Gok. 1998. "Health Service Utilization and Insurance Coverage: A Multivariate Probit Analysis." *Journal of the American Statistical Association*, 93(441): 63-72.
- Gourieroux, C., A. Monfort, and A. Trognon. 1984. "Pseudo Maximum Likelihood Methods: Theory." *Econometrica*, 52(3): 681-700.
- Greene, W. H. 1994. "Accounting for Excess Zeros and Sample Selection in Poisson and Negative Binomial Regression Models." *NYU Working Paper*, No. EC-94-10.
- Greene, W. H. 1995. "Sample Selection in the Poisson Regression Model." *NYU Working Paper*, No. EC-95-06.
- Greene, W. H. 2001. "FIML Estimation of Sample Selection Models for Count Data." in T. Negishi et al. (2001). *Economic Theory, Dynamics, and Markets - Essays in honor of Ryuzo Sato*, Kluwer Academic Publishers, pp. 73-92.
- Greene, W. H. 2003. *Econometric Analysis*. Prentice Hall, 5th edition.
- Grossman, M. 1972. "On the concept of health capital and the demand for health." *Journal of Political Economy*, 80: 223-255.
- Gurmu, S. 1997. "Semi-Parametric Estimation of Hurdle Regression Models with an Application to Medicaid Utilization." *Journal of Applied Econometrics*, 12: 225-242.
- Hadley, J. 2003. "Sicker and Poorer—The Consequences of Being Uninsured: A Review of the Research on the Relationship between Health Insurance, Medical Care Use, Health, Work, and Income." *Medical Care Research and Review*, 60(2): 3S-75S.
- Han, X. 2006. *Medical Expenditure Puzzle*. Society for Economic Dynamics, 2006 Meeting Papers.
- Hitiris, T., and J. Posnett. 1992. "The determinants and effects of health expenditure in developed countries." *Journal of Health Economics*, 11: 173-181.
- Holly, A. et al. 2005. "Out-of-Pocket Payments for Health Care Expenditures.", in A. Börsch-Supan et al. (2005) *Health, Aging and Retirement in Europe – First Results from the Survey on Health, Aging and Retirement in Europe*, MEA, pp. 126-132.
- Hunt-McCool, J., B. F. Kiker, and Y. C. Ng. 1994. "Estimates of the Demand for Medical Care Under Different Functional Forms." *Journal of Applied Econometrics*, 9(2): 201-218.
- Ismail, N., and A. A. Jemain. 2007. "Handling Overdispersion with Negative Binomial and Generalized Poisson Regression Models." *Casualty Actuarial Society Forum*, Winter 2007: 103-158.
- Jones, A. M. 2000. "Health Econometrics." in *Handbook of Health Economics*, 2000, vol. 1, Chapter 6, pp. 265-344.

- Jones, A. M., Koolman, X., and van Doorslaer, E. 2006. "The Impact of Having Supplementary Private Health Insurance on the Use of Specialists." *Annales d'Économie et de Statistique*, 83/84: 251-275.
- Manning, W. G. et al. 1987. "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment." *The American Economic Review*, 77(3): 251-277.
- Maurer, J. 2006. "Socioeconomic and Health Determinants of Health Care Utilization Among Elderly Europeans: A Semiparametric Assessment of Equity, Intensity and Responsiveness for Ten European Countries." *HEDG Working Paper*, No. 07/26, The University of York.
- Mossialos, E., and S. Thomson. 2004. *Voluntary health insurance in the European Union*. WHO, European Observatory on Health Systems and Policies.
- Murphy, K. M., and R. H. Topel. 1985. "Estimation and Inference in Two-Step Econometric Models." *Journal of Business and Economic Statistics*, 3(4): 370-379.
- OECD. 2004. *Private Health Insurance in OECD Countries*. The OECD Health Project.
- Paccagnella, O., V. Rebba, and G. Weber. 2008. "Voluntary Private Health Care Insurance Among the Over Fifties in Europe: A Comparative Analysis of SHARE Data." *Marco Fanno Working Paper*, No. 86, University of Padua.
- Pohlmeier, W., and V. Ulrich. 1995. "An Econometric Model of the Two-Part Decisionmaking Process in the Demand for Health Care." *The Journal of Human Resources*, 30(2): 339-361.
- Terza, J. V. 1998. "Estimating count data models with endogenous switching: Sample selection and endogenous treatment effects." *Journal of Econometrics*, 84: 129-154.
- Terza, J. V., A. Basu, and P. J. Rathouz. 2008. "Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling." *Journal of Health Economics*, 27: 531-543.
- Thomson, S., T. Foubister, and E. Mossialos. 2009. *Financing health care in the European Union*. WHO, European Observatory on Health Systems and Policies.
- Werblow, A., S. Felder, and P. Zweifel. 2007. "Population Ageing and Health Care Expenditure: A School of 'Red Herrings'?" *Health Economics*, 16: 1109-1126.
- Zimmerman Murphy, M. 1987. "The Importance of Sample Selection Bias in the Estimation of Medical Care Equations." *Eastern Economic Journal*, 13: 19-29.