Essays on Aging and Health

by

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Abstract

Life expectancy at older ages in Europe is increasing, and the share of elderly people in the total population is also rising. Therefore it is important to improve our understanding of the economic decisions made by the aging population. In this thesis I consider two economic decisions: the consumption decisions related to changing life expectancy, and decisions on health care utilization. I analyze how people aged 50 and above adjust their consumption expenditures if their subjective longevity changes, how their health care utilization depends on the coverage with voluntary private health insurance, and I also analyze the utilization of outpatient health care services related to the health care institutions.

The thesis consists of three chapters. All chapters are based on empirical work. In the empirical analysis I use the Survey of Health, Ageing and Retirement in Europe (SHARE) database. The SHARE is a cross-national panel database covering individuals aged 50 and above. The survey focuses on the socioeconomic and health status of the respondents. In this thesis I use the first two waves of the survey.

In the first chapter I estimate the effect of changes in subjective mortality hazard on consumption expenditures using the first two waves of the SHARE data. I measure mortality expectations with survey responses to a question on survival probability. To create plausibly exogenous variation in mortality hazard, I use the death of a sibling as an instrument. I find that a four-year decrease in the expected remaining lifetime at age 60 increases consumption by 7-9 percent in the subpopulation of individuals with positive financial wealth, who are likely not liquidity constrained. My results show that survey responses contain economically relevant information about longevity expectations, and confirm the predictions of life-cycle theories about the effect of these expectations on intertemporal choice.

In the second chapter I investigate if voluntary private health insurance coverage influences health care utilization in countries where the coverage ratio with public health insurance is high. I estimate this effect using the first wave of SHARE. Handling the potential endogeneity of voluntary insurance coverage and the large fraction of zero observations in the utilization models influences the empirical results. I show that the effect of private health insurance coverage on inpatient and outpatient care utilization is not trivial even in countries with generous public health funding. The main finding of this chapter is that voluntary private health insurance coverage increases dental care utilization, but decreases the visits to general practitioners. Private insurance is estimated to have little and insignificant influence on the utilization of inpatient care and outpatient specialist care. The magnitude of the effect of voluntary private health insurance

on health care utilization varies with the characteristics of the health care systems.

While in the first two chapters my aim is to estimate causal effects with an emphasis on the econometric methodology, the third chapter is more policy oriented. I analyze the relationship between health care institutions and the utilization of outpatient services by individuals aged 50 and above. I use cross-sectional data from the second wave of SHARE. The focus of this chapter is on the out-of-pocket costs of health care utilization, the gatekeeper role of general practitioners, and how these institutional settings are related to public and private care utilization. The results indicate that public financing has positive but moderate association with outpatient care utilization among the analyzed population. Copayments are related negatively to the probability of visiting a general practitioner among those in good health condition. I estimate the demand for private specialist care services to be higher in countries where there are copayments required for public specialist care, and where the general practitioners have gatekeeper role. These estimated effects on private specialist care utilization are relatively large, and are driven by the wealthier individuals.

In sum, the findings of this thesis indicate that the elderly people in Europe adjust their consumption expenditures if subjective longevity changes, and that their health care utilization is influenced in a non-trivial way by private health insurance coverage. Variations in the health care financing settings and the gatekeeper role of general practitioners are also related to the health care utilization of the people aged 50 and above, and these relations are heterogenous across the analyzed population.

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Introduction

According to a Eurostat forecast (Giannakouris (2008)), the share of people aged 65 years or over in the total population is projected to increase from 17.1% to 30.0% from 2008 to 2060 in the EU27 countries. The number of people aged 80 years or over is projected to almost triple from 2008 to 2060. These statistics indicate that it is important to improve our understanding of the economic decisions made by the aging population. In this thesis I analyze how consumption decisions are related to changing life expectancy, and decisions on health care utilization at older ages. I extend the literature in providing new evidence for the predictions of life-cycle theories using subjective longevity data, in establishing causal effects of voluntary private health insurance on health care utilization, and also in analyzing the utilization of private outpatient services among people aged 50 and above. All chapters are based on empirical work. In the empirical analysis I use the Survey of Health, Ageing and Retirement in Europe (SHARE) database.

In the first chapter I analyze the adjustment of consumption expenditures of elderly people if the subjective longevity changes. For this analysis I use the first two waves of the SHARE data. I measure mortality expectations with survey responses to a question on survival probability. To create plausibly exogenous variation in mortality hazard, I use the death of a sibling as an instrument. My empirical findings indicate that those who have positive wealth holdings adjust their consumption expenditures upwards if the subjective mortality hazard increases. I find that a four-year decrease in the expected remaining lifetime at age 60 increases consumption by 7-9 percent in the subpopulation of individuals with positive financial wealth, who are likely not liquidity constrained. This chapter contributes to the understanding of consumption behavior at older ages, and also to the application of subjective expectations data in empirical economic models. To my knowledge, it is a novelty in the literature to estimate the adjustment of consumption expenditures after a hazard shock on micro level data. My results show that survey responses contain economically relevant information about longevity expectations, and confirm the predictions of life-cycle theories about the effect of these expectations on intertemporal choice.

In the second chapter I investigate if voluntary private health insurance coverage influences health care utilization in countries where the coverage ratio with public health insurance is high. I estimate this effect using the first wave of SHARE. In most of the European countries there is almost universal coverage with public health insurance, and more than 50% of health expenditures are financed by the general government. Despite the broad coverage with public insurance,

the coverage rate with voluntary private health insurance is still not negligible in the countries analyzed. In the empirical analysis I model health care utilization as a two-stage decision, and take into account the potential endogeneity of voluntary private health insurance. This empirical approach is a contribution to the related literature. I identify the effect of PHI on health care utilization by using the assumption that only current employment characteristics influence the utilization, whereas past employment characteristics influence PHI coverage. Handling the potential endogeneity of voluntary insurance coverage and the large fraction of zero observations in the utilization models influences the empirical results. I show that the effect of private health insurance coverage on inpatient and outpatient care utilization is not trivial even in countries with generous public health funding. The main finding of this chapter is that voluntary private health insurance coverage increases dental care utilization, but decreases the visits to general practitioners. Private insurance is estimated to have little and insignificant influence on the utilization of inpatient care and outpatient specialist care. The magnitude of the effect of voluntary private health insurance on health care utilization varies with the characteristics of the health care systems.

The third chapter of this thesis is policy oriented, in which I analyze the relationship between health care institutions and the utilization of outpatient services by individuals aged 50 and above. In this analysis I use the second wave of SHARE. The focus of this chapter is on the out-of-pocket costs of health care utilization, the gatekeeper role of general practitioners, and how these institutional settings are related to public and private care utilization. The main novelty of this chapter is estimating how the selected characteristics of the public health care system are related to the utilization of private outpatient care. This analysis is possible since information on private care utilization is included in the SHARE data. The main results indicate the expected associations between the analyzed financing and organizational indicators, and public and private care utilization. More generous public financing generally implies higher demand for public care and lower demand for private care. There is also some evidence that cost-sharing implies higher utilization of specialist care, which can be due to the higher quality of services or to reverse causality. According to the estimation results if someone does not have any chronic health problem in the analyzed population then the copayments required for general practitioner services decrease the likelihood of visiting a public general practitioner by 13 percentage points, and the gatekeeping role decreases it by 11 percentage points. There are no such negative effects for those suffering from chronic illness. The estimated probability of visiting a private specialist is 4 percentage points higher if general practitioners act as gatekeepers, and 3 percentage points higher if there are copayments for specialist care. These effects are driven by people in the top financial wealth and income quartiles.

1. Subjective mortality hazard shocks and the adjustment of consumption expenditures

1.1. Introduction

Life expectancy at older ages is increasing. Life expectancy at age 65 has increased on average by four years between 1980 and 2008 in the European Union, increasing from 15.7 years to 19.7 years.[1] Increasing longevity has important consequences on the consumption and saving decisions of the elderly people. The standard life-cycle model with mortality risk implies that if people's longevity expectations change then their optimal level of consumption also changes.

In this chapter I analyze the adjustment of consumption expenditures of elderly people if the subjective longevity changes. In particular, I analyze if consumption is adjusted after a mortality hazard shock, and if this adjustment is in line with the implications of the life-cycle model. The life-cycle model with mortality risk predicts that the ex ante effect of mortality hazard on the expected consumption growth is negative: those who have higher hazard plan lower consumption level for the future, and consume more in the present, provided that the credit constraint is not binding. This is because higher mortality hazard has analogous effects as higher discount rate. Another implication of the model is that increasing hazard affects the consumption level positively: an increase in the hazard implies that it is optimal to consume more in the present, i.e. consumption should be adjusted. In this chapter I test these two implications of the life-cycle model. The individual level estimation results provide evidence for the predictions of life-cycle theories about the effect of subjective mortality hazard on intertemporal choice.

I use the first two waves of the Survey of Health, Ageing and Retirement in Europe (SHARE) in the empirical analysis. The SHARE is a cross-national panel database of individuals aged 50 and above. The two key variables used are expenditure on food as consumption measure, and the subjective survival probability to a given age. The latter variable is used to generate the subjective hazard indicators. The empirical specifications are based on the life-cycle model. Since the model has to be realistic for the elderly, typically retired individuals, I assume that the only source of uncertainty is the uncertain lifetime. Using further assumptions on preferences and wealth depletion, a closed form solution can be derived for the effect of subjective hazard on the consumption expenditures, otherwise the model can be solved only numerically.

I instrument the change in the hazard by the death of a sibling. The instrumenting strategy

[1] These statistics are based on the WHO European health for all database, and refer to countries which were members of the EU before 2004.

hinges on the observation that the death of a sibling influences the subjective survival probability, and such an event is not likely to have direct effect on the consumption expenditures of the elderly people. Instrumenting is needed since subjective hazard is endogenous in the consumption model due to the presence of measurement error and unobserved variables.

My empirical results show that those who have positive wealth holdings adjust their consumption expenditures upwards if the subjective mortality hazard increases. This effect is stronger if the oldest individuals are not included in the estimating sample, and also if those who are currently employed are excluded. The adjustment is estimated to take place through the expenditure on food consumed at home. To illustrate the magnitude of the estimated effects, at age 60 if the expected remaining lifetime decreases by 4 years then that is estimated to lead to around $200-220$ EUR increase in the annual expenditure on food at the median, ceteris paribus. This increase amounts to around $7-9\%$ of the median consumption expenditures. This estimated increasing effect is based on the subsample of individuals who have positive wealth holdings, therefore are likely not liquidity constrained. The estimated adjustment is stronger if the employed individuals and those receiving personal care or practical household help are excluded from the sample. Assuming that the adjustment of consumption expenditures after increasing and decreasing mortality hazard is symmetric, the empirical results indicate that increasing perceived longevity leads to smaller consumption expenditures, hence to slower wealth decumulation.

The estimated ex ante effect of mortality hazard on consumption dynamics is more sensitive to the empirical specifications, but again some evidence is found for the life-cycle effect. The Euler equation of the life-cycle model implies that the expected growth rate of consumption is lower if the current mortality hazard is higher. This estimated ex ante effect depends on the measure of increasing hazard included in the empirical model. If hazard shocks are indicated by a binary variable then the estimation results confirm the implications of the Euler equation.

To my knowledge, this chapter is the first in the literature to estimate the adjustment of consumption expenditures after a hazard shock on micro level data. The chapter is related to two strands of the literature: to empirical works which analyze the optimal consumption and saving profiles based on life-cycle models with mortality risk, and to the literature on applying subjective probability data in empirical economic models. The chapter contributes to the understanding of consumption behavior at older ages, and also to the application of subjective expectations data in empirical economic models.

A seminal article that introduces life-cycle models with mortality risk is of Yaari (1965). He derives the optimal consumption and saving dynamics under uncertain lifetime, with and without bequest motives and life insurance. Yaari shows that lifetime uncertainty can act analogously to increased impatience, but this may not hold if there are strong bequest motives or if wealth is restricted to be non-negative at the time of death. Hurd (1989) derives and estimates a life-cycle model with mortality risk and bequest motives. He assumes that there are borrowing constraints, and each individual receives fixed income flow. He finds based on data from the Longitudinal Re-

tirement History Survey that wealth is strongly (negatively) responsive to mortality rates. Using the Assets and Health Dynamics of the Oldest Old (AHEAD) data set, De Nardi et al. (2006) find that both differential life expectancy and expected medical expenditures have notable effect on asset accumulation. In their paper the authors compute survival probabilities from observed survival outcomes, and do not use self-reported survival probabilities. This chapter contributes to this literature in estimating the effect of changing hazard, using micro data.

Based on studies that use aggregate data, there is no consensus about the effect of increasing longevity on the aggregate consumption expenditures and savings. Skinner (1985a) shows on U.S. data that the life expectancy increased but the savings rates declined between 1970 and 1980. This finding contradicts the basic predictions of the life-cycle model. Skinner claims that bequest motives and life insurance can provide explanations for the decreasing saving rates. Bloom et al. (2003) also analyze the relationship between longevity and aggregate saving rates. They find some evidence from Asian and African countries that increasing life expectancy is associated with increasing savings rates. Li et al. (2007) derive that increasing longevity and rising old-age dependency rate affect the aggregate savings rate simultaneously and in the opposite direction. Their empirical results based on a panel of countries confirm that increasing longevity has positive effect on the saving rates, whereas higher old-age dependency rate has negative effect on that.

Using subjective survival data in empirical economic analysis is a relatively new phenomenon. Survey data is known to be first used by Hamermesh (1985) to investigate the determinants of subjective survival probability, and he emphasizes the potential importance of subjective survival data in analyzing life-cycle behaviors. Based on observations from two questionnaires he shows that subjective life expectancy corresponds to actuarial life expectancy (demographic consistency) and to forecasted change in life expectancy (expectational consistency). In addition, he also documents that there is a huge reliance on parents' longevity, and the effects of personal behavior (e.g. smoking) on expectations are consistent with the evidence of their effect on longevity. In my instrumenting strategy I use the reliance on the siblings' longevity.

Hurd and McGarry (1995) analyze responses to subjective survival probability questions based on the Health and Retirement Study (HRS). They find that average reported probabilities are comparable to statistical life tables, reported survival probabilities to ages 75 and 85 are internally consistent for most of the respondents, and the subjective probabilities covary with observable risk factors in the same way as actual outcomes do. Using the HRS data, Smith et al. (2001) show that subjective survival probabilities can predict future mortality relatively well. Manski (2004) also argues for applying subjective probabilistic data in empirical work. He points out that the widespread usage of models assuming that people maximize their expected utility calls for the measurement of subjective expectations. Manski claims based on findings from large-scale surveys that respondents are willing to answer questions about subjective expectations, and the answers are generally reasonable and internally consistent. In addition, he provides some evidence that reported expectations and individual or mean realiza-

tions match up relatively well. Elder (2007) is more sceptical about the reliability of subjective survival data. Based on the HRS data he points out that reported survival probabilities to old ages are systematically upward biased relative to life table data, and the predictive validity of reported probabilities are also lower at older ages. Nevertheless, he finds some evidence that subjective longevity influences economic behavior: higher life expectancy is estimated to increase the tolerance for volatility in investment portfolio returns. My results also confirm that subjective longevity influences the economic decisions.

Subjective survival probabilities are used among others by Gan et al. (2004) and Salm (2006) in the empirical analysis of life-cycle models. Both papers use data from the Health and Retirement Study. The basic research question of Gan et al. (2004) is similar to that of Hurd (1989), which is the empirical analysis of bequest motives. However, Gan et al. also analyze the explanatory power of subjective survival probability on consumption and wealth trajectories. They compare the out-of-sample predictions of the life-cycle model using subjective and life table probabilities, and find that the subjective survival probabilities can explain the observed consumption and saving decisions better. Salm (2006) also investigates the effect of subjective life expectancy on the consumption and saving decisions of older people, his approach is estimating the Euler equation derived from the life-cycle model. He also finds that the explanatory power of subjective expectations on consumption dynamics is higher than that of the statistical life table data. The contribution of this chapter is not only estimating the effect of changing subjective mortality hazard on the consumption expenditures, but also extending the analysis of consumption decisions to Europe.

The rest of the chapter is organized as follows. In section 1.2 I present the life-cycle model with mortality risk, which provides implications for the empirical analysis. The data and the variables used are presented in section 1.3. The estimation results are discussed in section 1.4, where I also discuss some potential caveats of the empirical model. A series of robustness checks are provided in section 1.6, and section 1.7 concludes.

1.2. The life-cycle model of consumption with uncertain lifetime

My purpose with the here presented life-cycle model is to derive implications for the empirical analysis: what factors influence the first differenced consumption, and what is the expected effect of increasing hazard. The modelling framework is related to life-cycle models with mortality risk, which are based on the article of Yaari (1965). Closely related models are developed also by Hurd (1989), Gan et al. (2004) and Salm (2006), who estimate life-cycle models with mortality risk and bequest motive. Salm (2006) also considers the effect of uncertain medical expenditures on consumption decisions.

The main deviation of the here presented life-cycle model from the cited models is that I derive the effect of mortality hazard shocks on the optimal level of consumption. I present a simple model in which there is a single composite consumption good. Income uncertainty,

medical expenditures and bequest motives are neglected. First, I derive the Euler equation of consumption dynamics, then solve the model for the optimal consumption level, then analyze how changing mortality hazard affects the optimal consumption level in this life-cycle model. Some extensions of the model are discussed in section 1.6.3.

The maximization problem of individual i is:

$$\begin{aligned} \max_{\{C_{it}, t=0...T_i\}} \; & E_0 \sum_{t=0}^{T_i} I_{it} \beta^t U(C_{it}) \\ \text{s.t. } & W_{it} = R(W_{it-1} - C_{it-1} + Y_i) \\ & 0 \leq W_{it}, \forall t = 1...T_i. \end{aligned} \tag{1.1}$$

C_{it} is consumption at time t, Y_i is time-invariant income, W_{it} is wealth, β is the discount factor, and R is one plus the interest rate. I_{it} is a binary indicator which equals one if individual i is alive at time t, zero otherwise. The expected value of this indicator is the subjective survival probability. T_i is the maximum remaining years of life for individual i, which can be considered as the difference between a maximum possible lifetime (say 120 years) and the individual's age. Thus T_i is not stochastic. The consumption, wealth, and income variables are conditional on survival to the given period, otherwise these values are zero. $U(C_{it})$ is the utility from consumption, assumed to be increasing and concave in C_{it}. Consumption and income realizations take place at the beginning of each time period, whereas death can happen at the turning points to new periods. The budget constraint is imposed since it is assumed that there are no credit facilities, which can be a reasonable assumption for older individuals. The constant, annuity-type income is also realistic for older individuals who receive pension income. E_0 denotes expectations at time 0.

The only uncertainty in the model is mortality risk. I assume that the individuals make their expectations on future survival using all the available information. They base their consumption decisions on these expectations. Using the law of iterated expectations, the expected value of future survival probabilities equals the current expectation on the survival, i.e. $E_0\left(E_t(I_{t+k}|I_t = 1)\right) = E_0(I_{t+k}|I_t = 1)$. This implies that only the current survival probabilities matter in the maximization problem. Based on these considerations, the maximand of model (1.1) can be rewritten:

$$\max_{\{C_{it}, t=0...T_i\}} \; \sum_{t=0}^{T_i} E_0\left(I_{it}\right) \beta^t U(C_{it}). \tag{1.2}$$

Another rationale for this simplification is that I_t is either 0 or 1. If $I_t = 0$ then $U(C_t) = C_t = 0$, thus only the $I_t = 1$ state matters, which occurs with probability $E_0(I_t)$.

The Bellman equation for the beginning of the tth period is:[2]

$$V(t, W_{it}) = U(C^*_{it}) + E_t\left(I_{it+1}\right) \beta V(t+1, R(W_{it} - C^*_{it} + Y_i)), \tag{1.3}$$

[2] The time argument is included in the value function because of the finite horizon.

where C^* denotes the optimal level of consumption, and the value function is conditional on survival to period t. The Lagrangian of the optimization problem under (1.1), using expression (1.2) is:

$$\Lambda_{it} = U(C_{it}) + E_t\left(I_{it+1}\right)\beta V(t+1, R(W_{it} - C_{it} + Y_i)) + \lambda_{it}(W_{it} - C_{it} + Y_i). \tag{1.4}$$

The first-order optimality conditions are:

$$\begin{aligned} \frac{\partial U(C_{it})}{\partial C_{it}} - E_t\left(I_{it+1}\right)\beta R\frac{\partial V(t+1, W_{it+1})}{\partial W_{it+1}} - \lambda_{it} = 0 \\ W_{it} - C_{it} + Y_i \geq 0, \lambda_{it} \geq 0, \\ \lambda_{it}(W_{it} - C_{it} + Y_i) = 0. \end{aligned} \tag{1.5}$$

Differentiating equation (1.3) with respect to W_{it} gives:

$$\frac{\partial V(t, W_{it})}{\partial W_{it}} = \left[\frac{\partial U(C^*_{it})}{\partial C^*_{it}} - E_t\left(I_{it+1}\right)\beta R\frac{\partial V(t+1, W_{it+1})}{\partial W_{it+1}}\right]\frac{\partial C^*_{it}}{\partial W_{it}} + E_t\left(I_{it+1}\right)\beta R\frac{\partial V(t+1, W_{it+1})}{\partial W_{it+1}}. \tag{1.6}$$

Substituting the first condition under (1.5) into (1.6) gives:

$$\frac{\partial V(t, W_{it})}{\partial W_{it}} = \lambda_{it}\frac{\partial C^*_{it}}{\partial W_{it}} + E_t\left(I_{it+1}\right)\beta R\frac{\partial V(t+1, W_{it+1})}{\partial W_{it+1}}. \tag{1.7}$$

If the credit constraint is binding, then $\lambda_{it}\frac{\partial C^*_{it}}{\partial W_{it}} = \lambda_{it}\cdot 1 = \lambda_{it}$, otherwise $\lambda_{it}\frac{\partial C^*_{it}}{\partial W_{it}} = 0\cdot\frac{\partial C^*_{it}}{\partial W_{it}} = \lambda_{it}$. Therefore from (1.7) and (1.5):

$$\frac{\partial V(t, W_{it})}{\partial W_{it}} = \lambda_{it} + E_t\left(I_{it+1}\right)\beta R\frac{\partial V(t+1, W_{it+1})}{\partial W_{it+1}} = \frac{\partial U(C_{it})}{\partial C_{it}}. \tag{1.8}$$

Rewriting equation (1.8) gives the Euler equation:

$$\frac{\partial U(C_{it})}{\partial C_{it}} = E_t\left(I_{it+1}\right)\beta R\frac{\partial U(C_{it+1})}{\partial C_{it+1}} + \lambda_{it}. \tag{1.9}$$

Let's assume that the utility of current consumption is of the constant relative risk aversion (CRRA) form: $U(C_{it}) = \frac{C_{it}^{1-\gamma}}{1-\gamma}$, where $\gamma > 0$ is the coefficient of relative risk aversion, and its reciprocal is the intertemporal elasticity of substitution. Using this assumption, the Euler equation (1.9) can be rewritten:

$$C_{it}^{-\gamma} = E_t\left(I_{it+1}\right)\beta R C_{it+1}^{-\gamma} + \lambda_{it}. \tag{1.10}$$

Rearranging this expression, provided that the credit constraint is not binding, and using the

law of iterated expectations give:

$$\begin{aligned} \frac{C_{it+1}}{C_{it}} &= \left(E_t\left(I_{it+1}\right)\beta R\right)^{\frac{1}{\gamma}}, \\ C_{it} &= C_{i0}E_0(I_{it})^{\frac{1}{\gamma}}\left(\beta R\right)^{\frac{t}{\gamma}}. \end{aligned} \tag{1.11}$$

Equation (1.11) holds only if the wealth is not zero. If an individual has zero wealth level then the consumption equals the income in every period. The Euler equation reflects that a consequence of lifetime uncertainty is that future is discounted to a higher extent. This result is derived also by Yaari (1965). A linearized version of equation (1.11) extended with the uncertainty of medical expenditures is estimated by Salm (2006). The Euler equation describes the expected consumption path, conditional on survival. However, the survival probability can change as the time elapses, thus the optimal consumption path can also change. The Euler equation per se cannot reflect the effect of changing survival probability on the optimal consumption path.

The next step is to derive the optimal level of current consumption. I assume that the expected value of the survival indicator is a power function of the life table (objective) survival probability. This assumption is equivalent to the hazard-scaling approach of Gan et al. (2003), which is discussed in further details in section 1.3.2. Denote with η_{i0} the individual specific index of pessimism at time 0, and with S_t^{t+k} the life table survival probability from time t to time $t+k$. To simplify the notations, I denote the subjective survival probability of individual i from time t to time $t+k$ with s_{it}^{t+k}, thus $E_0(I_{it}) = s_{i0}^t$. It follows that $s_{i0}^t = (S_0^t)^{\eta_{i0}}$. Denoting the subjective cumulative hazard of dying for individual i between periods t and $t+k$ with h_{it}^{t+k}, and using the definition that $\ln s_{it}^{t+k} = -h_{it}^{t+k}$, equation (1.11) can be rewritten:

$$\ln C_{it+1} - \ln C_{it} = \frac{1}{\gamma}\ln\left(\beta R\right) - \frac{1}{\gamma}h_{it}^{t+1} = \frac{1}{\gamma}\ln\left(\beta R\right) + \frac{1}{\gamma}\eta_{i0}\ln S_t^{t+1}. \tag{1.12}$$

This is the Euler equation which describes the planned, ex ante dynamics of consumption based on the assumptions on the preferences and on the functional form of the subjective survival probability.

No general closed form solution exists for the optimal consumption level, because it might be optimal to deplete the wealth at some point during the lifetime (before period T_i), and from that point on the Euler equation (1.11) does not hold. Thus the optimization problem can be solved only numerically, as done also by Gan et al. (2004) for a similar life-cycle model. However, conditional on the time of depletion ($T_i^* \leq T_i$), a closed form solution can be derived for the optimal consumption level. Since there is no bequest motive, wealth is depleted at time T_i, at the latest. It is optimal not to deplete the wealth before T_i if the ratio of initial wealth holdings (W_{i0}) to the income (Y_i) is large, and if the expected remaining lifetime of the individual is high (for details see also Hurd (1989)). T_i^* depends also on the discount and interest factors, and on the coefficient of relative risk aversion.

Using the $W_{iT_i^*} = 0$ condition gives that

$$\sum_{t=0}^{T_i^*} \left(-\frac{C_{it}}{R^t} + \frac{Y_i}{R^t} \right) + W_{i0} = 0. \tag{1.13}$$

I assume that the Euler equation holds exactly until time T_i^*, wealth is depleted with consumption C_{iT^*} at T_i^*, and from that point on the consumption equals the income.[3] Substituting the Euler equation from equation (1.11) into equation (1.13) and using the hazard-scaling assumption give the expression of optimal current consumption:

$$C_{i0} = \frac{W_{i0} + Y_i \frac{1-R^{T_i^*+1}}{R^{T_i^*}-R^{T_i^*+1}}}{\sum_{t=0}^{T_i^*} \frac{\left(S_0^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t}{\gamma}}}{R^t}}. \tag{1.14}$$

Based on this expression the partial effect of the pessimism index on the level of initial consumption is positive, thus the partial effect of subjective hazard is also positive. The planned period one consumption level is $C_{i1} = C_{i0} \left(\left(S_0^1\right)^{\eta_{i0}} \beta R \right)^{\frac{1}{\gamma}}$.

My aim is to analyze the effect of unexpected changes in subjective hazard on consumption level. A hazard shock can be represented by an unexpected change in the pessimism index (η_i). In its simplest version, the life-cycle model predicts that the effect of a negative shock in subjective survival probability on the optimal consumption level is positive, and consequently, the effect of higher hazard is also positive. Assume that an upward shock affects the subjective hazard at the beginning of period one. This shock can be represented by increasing η_{i0} to η_{i1}. First I also assume that the time point of wealth depletion is only marginally affected by the hazard shock, and remains approximately equal to T_i^*. It can be derived using the expression of optimal initial consumption level (equation (1.14)) that the optimal consumption level at period one is

$$C_{i1} = RC_{i0} \frac{\sum_{t=0}^{T_i^*} \frac{\left(S_0^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t}{\gamma}}}{R^t} - 1}{\sum_{t=1}^{T_i^*} \frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}} (\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}}. \tag{1.15}$$

Using that $S_0^t = S_0^1 \cdot S_1^t$, it follows that the ex post difference between the consumption levels of the first two periods is

$$\ln C_{i1} - \ln C_{i0} = \frac{1}{\gamma} \ln (\beta R) - \frac{1}{\gamma} h_{i0}^1 + \ln \left(\sum_{t=1}^{T_i^*} \frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}} \right) - \ln \left(\sum_{t=1}^{T_i^*} \frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}} (\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}} \right). \tag{1.16}$$

[3] The individual has two decison variables: C_{i0} and T_i^*. Based on the assumption of exact depletion the second identifying equation can be written down, and the tradeoff between the initial consumption level and the time of wealth depletion before T_i can be analyzed. $C_{iT_i^*} = C_{i0} \left(S_0^{T_i^*}\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{T_i^*}{\gamma}}$ from the Euler equation, and $C_{iT_i^*} = Y_i$ from the assumption of exact depletion at time $T_i^* < T_i$. Therefore $\frac{Y_i}{C_{i0}} = \left(S_0^{T_i^*}\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{T_i^*}{\gamma}}$, which shows that given income and initial consumption, T_i^* has to decrease if the mortality hazard increases (η_{i0} increases). In addition, if the life table cumulative survival probability were a power function of the one-period survival probability then the tradeoff between C_{i0} and T_i^* would be exponential.

This expression shows that three mechanisms drive the consumption dynamics: first, the time preferences and the interest rate, second, the one period hazard which shows the effect of moving one period further in the lifetime, and finally, the hazard shock also influences the dynamics.

If the credit constraint is not binding then the differenced logarithmic consumption depends negatively on the initial hazard level, but an upward hazard shock ($\eta_{i1} > \eta_{i0}$) has positive effect on it. This solution is based on the assumption that the hazard shock does not considerably affect the optimal time point of wealth depletion. This is a simplifying assumption. However, if T_i^* is large, and the hazard shock is moderate then equation (1.16) can still be a good approximation for the consumption dynamics. In addition, if the ratio of initial wealth to income is high then $T_i^* = T_i$ is also unaffected. Otherwise T_i^* decreases after the upward hazard shock, which makes the last term in equation (1.16) even smaller. Thus the expression under equation (1.16) can be considered as a lower bound of the ex post difference in the optimal logarithmic consumption expenditures.

I apply linear approximation of the differenced logarithmic term in equation (1.16) at η_{i0}:

$$\ln\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right)-\ln\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right)\approx$$

$$\approx(\eta_{i0}-\eta_{i1})\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right)^{-1}\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\ln S_1^t\right)=$$

$$=\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right)^{-1}\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\left(-\eta_{i1}\ln S_1^t+\eta_{i0}\ln S_1^t\right)\right). \tag{1.17}$$

Since $-\eta_{i1}\ln S_1^t$ equals the cumulative hazard from period 1 to period t after the hazard shock, and $-\eta_{i0}\ln S_1^t$ equals the cumulative hazard before the hazard shock, substituting this approximation to equation (1.16) implies that the first differenced logarithmic consumption depends on the first differenced mortality hazard. Equation (1.17) also shows that the effect of the first differenced hazard is heterogenous, it depends on the initial survival probability.

Motivated by the consumption model of equation (1.16), and using the approximation of equation (1.17), two versions of empirical consumption models will be estimated:

$$d\ln C_{i1} = \alpha_{01}+\alpha_{11}h_{i0}+\alpha_{21}dh_{i1}+u_{1i} \tag{1.18}$$

$$d\ln C_{i1} = \alpha_{02}+\alpha_{12}h_{i0}+\alpha_{22}H_i+u_{2i}. \tag{1.19}$$

In these models h_{i0} and h_{i1} are the one period hazard indicators at time 0 and 1, and in the second specification H_i is a binary indicator of increasing hazard between periods 0 and 1.[4] As a simplification, I neglect the heterogeneity in the effect of the indicators of changing hazard.

[4] Using dh_{i1} in equation (1.18) is also a simplification, which can support the interpretability of the empirical results. Apart from hazard shocks, the hazard increases due to aging, which effect is also included in dh_{i1}. Using the differenced hazard instead of a "pure" measure of hazard shock can cause downward bias in the estimated effect in the empirical model.

Based on the life-cycle model the α_{11} and α_{12} parameters are negative, whereas the α_{21} and α_{22} parameters should be positive if the credit constraint is not binding. If the credit constraint is binding then these parameters should be zero. Model (1.18) is based on the linear approximation of equation (1.16), whereas model (1.19) allows us to test the implication of the life-cycle model that the consumption expenditures should increase after an upward hazard shock.

The consumption model extended with hazard shocks is comparable to those consumption models in the literature where the consumption differences depend on intertemporal substitution, and also on changing expectations about future incomes. The adjustment of consumption after shifts in permanent income is analyzed among others by Flavin (1981) and Campbell and Deaton (1989). Parker and Preston (2005) decompose consumption growth into four factors, one of which is the effect of new informations. Here I assume that individual income is constant, but analyze the adjustment after changing subjective mortality hazard, which can be considered as adjustment after the arrival of new informations.

The result presented under equation (1.16) is an approximation, and cannot reveal the effect of a hazard shock on the optimal period of wealth depletion. If wealth is allowed to be depleted before time T_i then the exact solution of the consumption model can be found only numerically. Nevertheless, numerical results still indicate that the effect of an upward hazard shock on consumption expenditures is positive, and also that an upward hazard shock might decrease T_i^*. As a numerical example, using parameter values of $R = 1.05$, $\beta = 0.95$, $T = 20$, $\gamma = 2$, $Y = 20$, and $W_0 = 180$, Figure 1.1 illustrates how a change in mortality hazard affects the optimal consumption level and consumption path. The selected income and wealth values correspond to the observed data means in thousands. In this example I assume constant one-period hazard. The ex ante consumption path is the solid line, whereas the ex post path is the dashed line. The upward hazard shock makes the path steeper, and the level of period one consumption is shifted upwards. At the same time, the wealth is depleted earlier, which also allows for increasing the consumption level at period one. This example reinforces that the life-cycle model implies a positive effect of increasing hazard on consumption, and also that the higher hazard level decreases the planned consumption level for the future.[5]

[5] The upward shift in the optimal consumption level depends on the parameters in the model. The following table presents how much does the consumption level at period 1 increase if the one period hazard increases from 0.1 to 0.2 (the survival probability decreases from 0.9 to 0.8), and $R = 1.05, \beta = 0.95, T = 20, Y = 20$.

	$W = 20$	$W = 180$	$W = 400$
$\gamma = 0.5$	0	51	74
$\gamma = 0.9$	5	21	42
$\gamma = 2$	0	13	25

These results clearly show that the effect of an upward hazard shock on the optimal consumption level is positive, but this effect depends on the wealth level relative to income and on the preference parameters.

Holding the income fixed, if the wealth level is higher then the optimal consumption level is more sensitive to the hazard shock. The sensitivity is not a monotone function of the coefficient of relative risk aversion, but at higher realtive wealth holdings the effect of shock decreases with the risk aversion coefficient.

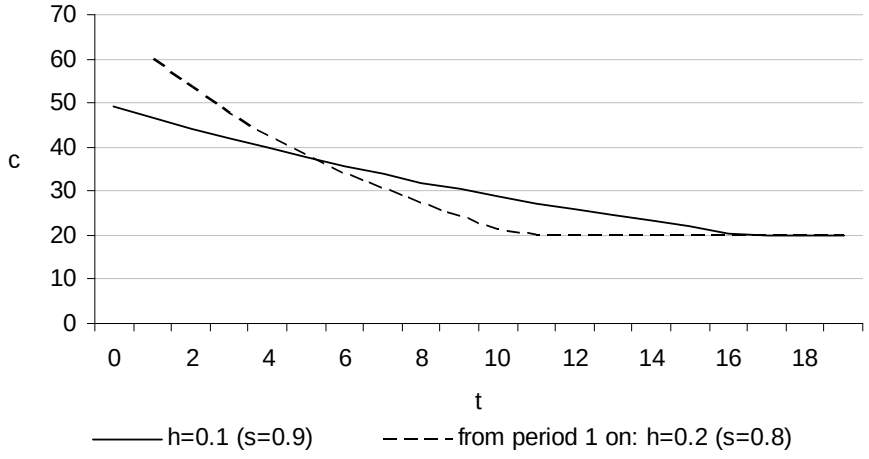


Figure 1.1: Numerical example: effect of a change in mortality hazard

1.3. Data

The empirical analysis is based on the first two waves of the Survey of Health, Ageing and Retirement in Europe.[6] The SHARE is a panel database covering individuals aged at least 50, and their spouses. The first wave of the data was collected in year 2004, and the survey is repeated every second year. It is a multidisciplinary database with a structure similar to the U.S. based Health and Retirement Study (HRS). The focus of the questionnaire is on the health, socioeconomic status, social and family networks of the respondents. I include those countries in the analysis for which both the first and second wave data are available. Therefore eleven countries can be included: Austria, Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain, Sweden, and Switzerland. The number of individuals for whom the relevant variables are available in both waves is 16 thousand. I use unweighted data.

The consumption models are estimated on the subsample of individuals aged between 50 and 80 in the second wave of the survey. I exclude those individuals who are aged above 80 the second wave (around 7% of the sample). The reason for this restriction is that the subjective mortality hazard indicator is less reliable for the oldest individuals. The question about subjective survival probability might be more difficult for them to answer, the higher nonresponse rate also reflects this problem. The following statistics and results refer to the restricted estimation sample, however, in section 1.6.1 I present a robustness check with respect to the age restriction.

[6] This thesis uses data from SHARE release 2.3.1, as of July 29th 2010. 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).

1.3.1. Variables used

Table 1.1 includes some descriptive statistics of the variables used in the empirical analysis. These are the measures of consumption expenditures, and such variables which can have influencing effect on the difference in consumption expenditures between the two waves. The financial variables (consumption, income, and wealth) are purchasing parity adjusted annual amounts, deflated to year 2005 Euros. These variables are generated as the mean of the five imputed values provided in the SHARE database. Using the average of the imputed values is a simplification which can cause some downward bias in the standard error estimates. The household level consumption, income and wealth measures are divided by the household size, so that these can represent individual amounts.

	Mean	Median	Standard dev.
consumption (1000 EUR)	2.96	2.56	1.89
income (1000 EUR)	21.56	13.40	99.06
net worth (1000 EUR)	180.38	88.61	535.34
ln(consumption)	7.84	7.85	0.62
dln(consumption)	-0.02	-0.02	0.65
survival prob. (%)	64.31	70.00	27.49
age	63.33	63.00	8.30
female	0.54	1	0.50
new chronic disease	0.13	0	0.33
become ADL limited	0.04	0	0.20
d(depression)	-0.02	0	0.45
exit employment	0.05	0	0.21
become single	0.01	0	0.12
Observations: 49,496			

Table 1.1: Descriptive statistics, first two waves of SHARE

Consumption is measured by annual expenditure on food at home and outside home.[7] Outlying consumption values are excluded from the empirical analysis, where an observation is defined to be outlier if the absolute value of the first differenced consumption is larger than 5 thousand EUR (2.4% out of those second wave respondents for whom the differenced consumption is not missing). Measuring consumption by expenditures on food is a data limitation since the SHARE does not ask about overall or other categories of consumption expenditures. Based on Eurostat statistics for year 2006 the expenditure on food is around 13% of overall household expenditures in the European Union. Nevertheless, the food expenditure indicator can serve as a proxy for overall consumption expenditures, and measures of expenditure on food can be relatively reliable.

If the utility function is additively separable in food and other consumption goods then the results of the life-cycle model of consumption are valid for food consumption. Additive separability is assumed by Zeldes (1989) when testing the permanent income hypothesis. Browning and Lusardi (1996) provide a literature overview of Euler equation consumption studies, and

[7] The wording of the question is the following: "Thinking about the last 12 months: about how much did your household spend in a typical month on food to be consumed at/outside home?" This amount is multiplied by 12 to generate the annual amount.

document that using food consumption data is widespread in the literature. There is some evidence in the literature that food consumption is less elastic than other categories of non-durable consumption, therefore my empirical results are likely to underestimate the adjustment in overall consumption. Regmi et al. (2001) provide international evidence that the income elasticity of food consumption is lower than of other consumption categories in low, middle, and high income countries as well. Browning and Crossley (2000) show that luxury goods have higher intertemporal elasticity of substitution, hence this elasticity is relatively low for food consumption.

Income is measured as total gross income, which includes income from employment, pension, regular transfers, capital asset incomes and received rent payments as well. The life-cycle model presented in section 1.2 is based on the assumption of time-invariant income, although the observed nominal income varies between the two waves. However, 72% of the individuals in the estimation sample receive pension income, which can be considered as annuity. Among those single individuals who receive pension, the mean ratio of pension income to total income is 80%, and the median is 95%. Thus the majority of the sample consists of pensioners, for whom the dominant source of income is the pension income.

The indicators of new chronic diseases are binary variables which equal one if the individual reports having heart attack, stroke, hip fracture or the diagnosis of high blood pressure, cancer, diabetes, high blood cholesterol since the first interview. Only 13% of the respondents report being diagnosed with any of these conditions since the first interview. Two additional health measures are used, which are indicators of reporting limitations with activities of daily living (ADL), and whether the respondent suffers from depression.[8] The becoming single indicator is set to one if the respondent was married and living together with the spouse in the first wave, but his marital status is widowed, divorced or married but living separated from the spouse in the second wave. Exiting employment is also a binary variable which equals one if a respondent was employed or self-employed in wave 1 but not in wave 2.

The variables of central interest are the subjective survival probability and mortality hazard generated from the reported probability. As I discuss in section 1.3.2, not the reported survival probability but an adjusted value is used in the estimations. The wording of the survival probability question is "What are the chances that you will live to be age [target age] or more?", where the target age depends on the age of the respondent (with values between $75-110$). This question is included in the expectations section of the questionnaire. The introduction to this block is a warm-up question about the chances for sunny weather on the following day. This might help respondents in answering probabilistic questions. The item nonresponse rate to the survival probability question is around 8% in both waves.

1.3.2. Measuring subjective hazard

Using the level or the change of reported survival probability in the empirical models could lead to unreliable results. The main reason is that due to survey design the difference between the

[8] The SHARE data includes a binary indicator of depression, based on the EURO-D scale of depression.

target age and the current age of the respondents varies across ages. The reported survival probability can change not only if the subjective life expectancy changes, but also if the target age in the probability question changes. Therefore the reported probabilities should be adjusted. In addition, an important problem related to probabilistic survey questions is the high proportion of focal responses (0, 50 or 100 percentage reported probabilities).

One potential approach for adjusting the reported probabilities is suggested by Hill et al. (2004). The authors apply the so-called modal response hypothesis, i.e. the respondents are assumed to report the probability which is the most likely among the possible probabilities. They show that focal responses become more likely with increasing uncertainty. Using cross-sectional HRS data they apply maximum likelihood estimation to estimate the distribution of beliefs, conditional on a set of individual characteristics.

A different approach is suggested by Gan et al. (2003). They derive a "hazard-scaling" and alternatively an "age-scaling" index, which are used to derive the individual subjective survival curves. In addition, due to the large proportion of focal responses they apply a Bayesian approach to obtain the posterior density of the underlying subjective survival probability. The authors make use of the observed death records in the HRS data when estimating the expected value of the posterior subjective survival probability. This approach of probability adjustment is applied by Gan et al. (2004) and Salm (2006) when analyzing consumption and wealth dynamics.

I apply a similar adjustment method as Salm (2006) does. The reported probability is adjusted so that for each individual it represents the subjective probability of living at least two years more. I do not make any further adjustment in the reported probability, assuming that the reported probability includes all the available information about the subjective survival beliefs.

The adjustment procedure is based on the hazard-scaling approach of Gan et al. (2003), which also corresponds to the assumptions made in the life-cycle model of section 1.2. It is assumed that the individual hazard function equals the life table hazard function multiplied by a constant. The first step is to derive the individual specific index of pessimism:

$$\eta_i = \frac{\ln \tilde{s}_{it}^{t+a}}{\ln S_t^{t+a}}, \tag{1.20}$$

where the notations follow those of section 1.2, t is the current age, and $t+a$ is the target age, $\tilde{s}$ is the reported survival probability, and S is the life table survival probability. The WHO life tables for year 2006 are used, which are gender and country specific life tables.[9] Based on the WHO life tables the survival probabilities can be determined only for 5-year age ranges. In order to calculate the survival probability to any age I make the simplifying assumption that the number of people alive from a given cohort declines linearly within the given 5-year intervals.

[9] The source of the life tables is: http://apps.who.int/whosis/database/life_tables/life_tables.cfm. These are period (or current), and not cohort life tables. Period life tables might underestimate the survival probabilities to old ages. Since the life tables are used only for adjusting the reported probabilities, using period life tables does not cause any bias in the estimates.

The 2-year subjective survival probability of individual i is calculated the following way:

$$s_{it}^{t+2} = \left(S_{it}^{t+2}\right)^{\eta_i}, \tag{1.21}$$

and the 2-year cumulative hazard is

$$h_{it}^{t+2} = -\eta_i \ln S_{it}^{t+2}. \tag{1.22}$$

The 2-year difference between the target and current age is specified because on average two years elapse between the two observations of consumption expenditures. The Euler equation (equation (1.12)) implies that the estimated intertemporal elasticity of substitution can be obtained if the two-year hazard is included in the consumption model.

The pessimism index cannot be calculated for those who report 0% (almost 5% of the respondents of the estimation sample report 0% survival probability in either the first or second wave survey). Therefore the adjusted mortality hazard is missing for them. When estimating the consumption models I exclude those respondents for whom the subjective hazard is missing, but in section 1.6.1 I analyze how sensitive the results are to assuming that the 0% reported probability is due to rounding, and the real subjective survival probability is 0.5%.

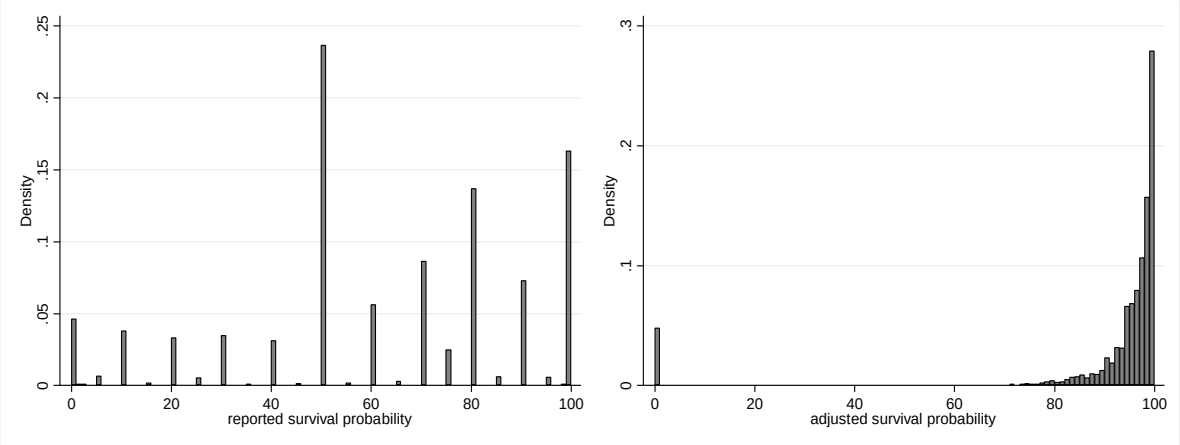


Figure 1.2: Histograms of the reported and adjusted survival probabilities, pooled data

The correlation between the reported and generated survival probability is 0.64 (if the zero reported probabilities are excluded then it is 0.79). The histograms of these two variables are presented in Figure 1.2, where the assumption is used that the 0% reported probability corresponds to 0.5% true probability. The adjusted survival probability is more skewed to the right than the original one because it refers to 2-year survival probability, which is a shorter period than the average difference between the target and current age in the questionnaire. The mean of the difference between the current and target age in the survey is 15.3. The spikes above 0% and below 100% survival probability disappear due to the adjustment procedure.[10]

[10] The spike at 100% survival probability remains, which is a consequence of the adjustment procedure. The

The histogram of the reported survival probabilities clearly show the problem of focal responses, which indicates measurement error.

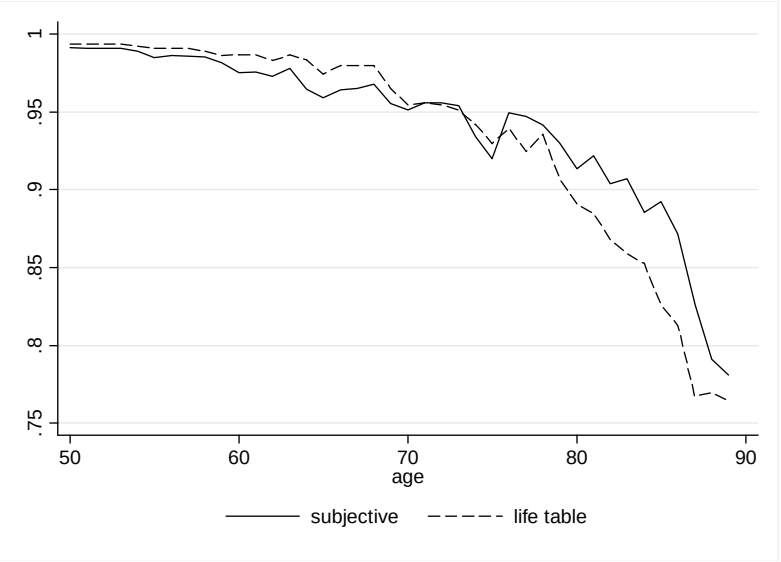


Figure 1.3: Median of subjective and life table 2-year survival probabilities as function of age

A comparison between the life table and reported subjective survival probabilities is provided by Figure 1.3. The figure depicts the median of the subjective and life table 2-year survival probabilities by age, below age 90. The life table probabilities are based on the WHO data. The subjective survival probabilities are based on the above described adjustment procedure. The figure is comparable to the figures reported by Borsch-Supan et al. (2005), p. 336. It indicates that the reported probabilities fit the life table probabilities relatively well, and the 2-year survival probabilities are close to one, especially at younger ages. However, there is some evidence that people overestimate their survival probability at older ages, whereas there is slight underestimation at younger ages.

In Table 1.2 I present the estimated coefficients of three OLS models. These models show how the subjective hazard indicators correspond to the death of relatives, to the parents' longevity, and to other individual specific characteristics. The estimating sample used here is the same as in the empirical consumption model: those aged above 80 are excluded, and also for whom the value of differenced consumption is outlier. In the first part of the table I use two indicators of increasing hazard: the first differenced adjusted hazard, and a binary indicator of an at least 1.5 percentage points drop in the adjusted subjective survival probability between the first and second waves of the survey. There is one outlier value with hazard increase above 5, this observation is excluded from the estimations. The binary indicator of increasing hazard equals one for 29% of the respondents in the estimation sample. 1.5 percentage points decrease in the

pessimism index (η) equals zero for those who report 100% survival probability, thus the adjusted survival probability (s) also equals 100%.

On the other hand, the spike at 50% can not be seen any more because the difference between the target and current age varies across the individuals, thus the reported 50% survival probability corresponds to varying 2-year survival probability.

two-year survival probability is on average similar to 10 percentage points decrease in the ten-year survival probability. In the second part of the table the dependent variable is the first wave adjusted hazard. The significance levels are based on clustered standard errors, with clustering on the household level.

The included regressors are variables that might influence the hazard indicators. My focus is on the indicators of the death of a sibling between the two survey waves, and the death of all siblings before wave one. These indicators will serve as instruments in the consumption model. The death of a sibling between the two survey waves is used as instrument for increasing subjective hazard. For 10% of the respondents in the estimation sample the number of siblings alive decreases between the two waves, and the observed decrease is less than three. The change in the number of siblings alive is a noisy measure, therefore I consider as noise the differences higher than three.[11] The level of first wave hazard is regressed among others on a binary variable which equals one if the respondents has no siblings alive in wave one, but reports that he had siblings before (5% of the respondents in the estimation sample).

Based on these estimations the respondents update their survival probabilities if a sibling dies, the death of a sibling has significantly positive effect on the subjective mortality hazard. This effect is stronger if the binary indicator of increasing hazard is used. The estimation results imply that for a 60 year old representative man the expected remaining lifetime decreases by around 2.4 years after the death of a sibling, ceteris paribus. The death of a parent has also positive effect on the subjective hazard, but this effect is weaker. Only few of the indicators of newly diagnosed diseases have significant effect on the hazard, which might be due to the few observations on new diagnosis.

The estimation results indicate that if the respondent had siblings but all of them are dead by wave one then the subjective mortality hazard is significantly higher. The magnitude of this effect is close to the positive effect the death of a sibling between the two survey waves has on the hazard. The age or age at death of a parent has also significant effect on the hazard, this effect is negative. The health indicators have the expected effect on subjective hazard: having been diagnosed with chronic health conditions, having ADL limitations or symptoms of depression increase the subjective mortality hazard, and this effect is significant for most of the health problems.

The presented results are in line with the findings of Hamermesh (1985) and Hurd and McGarry (1995): the observed health problems have positive effect on the hazard measure, which indicates that this is a reliable measure of the subjective hazard. At the same time, the subjective hazard is estimated to depend on the longevity of the relatives.

[11] For 751 respondents the observed change in the number of siblings alive between the two waves is positive, which indicates measurement error in this variable. For 167 respondents the observed decrease is more than three.

	diff. hazard	increasing hazard		hazard
sibling dies	0.007***	0.057***	all siblings dead	0.006**
	[3.11]	[4.19]		[2.44]
mother dies	0.002	0.040**	age mother	-0.000***
	[1.31]	[2.33]		[5.23]
father dies	0.002	0.052**	age father	-0.000**
	[1.12]	[2.40]		[2.57]
age	0.000	0.012***	age	0.002***
	[0.23]	[23.16]		[30.95]
female	-0.004***	-0.020***	female	-0.003***
	[3.85]	[2.66]		[3.43]
new cancer	0.019**	0.182***	had cancer	0.006***
	[2.45]	[2.72]		[2.72]
new heart attack	0.022**	0.168***	had heart attack	0.012***
	[2.07]	[2.87]		[6.54]
new stroke	-0.009	-0.046	had stroke	0.007**
	[0.64]	[0.45]		[2.21]
new fracture	0.008	0.057	had hip fracture	0.003
	[0.59]	[0.41]		[0.59]
new hypertension	0.004**	0.019	had hypertension	0.002**
	[1.97]	[1.45]		[2.55]
new high cholesterol	0.001	-0.01	had high cholesterol	0.003***
	[0.41]	[0.69]		[2.67]
new diabetes	-0.009**	-0.040*	had diabetes	0.007***
	[2.49]	[1.82]		[3.50]
dADL	0.004	0.088***	ADL	0.009***
	[0.98]	[4.21]		[3.83]
ddepression	0.006***	0.045***	depression	0.010***
	[5.27]	[5.22]		[9.31]
exit emp	0.001	0.040***	employed	-0.004***
	[1.02]	[2.74]		[4.79]
become single	0.005	0.065**	single	0.002**
	[1.35]	[2.29]		[2.13]
Constant	0.008	-0.433***	Constant	-0.082***
	[1.54]	[11.56]		[14.79]
Observations	13,223	13,891	Observations	12,665
R-squared	0.01	0.06	R-squared	0.21

Absolute value of cluster robust t statistics in brackets

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

Table 1.2: OLS models of changing subjective mortality hazard and hazard level, country dummies not reported

1.4. Estimation results

1.4.1. Empirical specification

In this chapter I analyze how the hazard level and increasing mortality hazard affect the consumption expenditures of older individuals. Using the first two waves of the SHARE data this effect can be analyzed by estimating cross-sectional regressions of the first differenced consumption on mortality hazard indicators. The estimated models are based on equations (1.18) and (1.19). I use two indicators of increasing hazard: the first differenced adjusted hazard, and a binary indicator of an at least 1.5 percentage points drop in the adjusted two-year subjective survival probability between the first and second waves of the survey. Thus there are two specifications of the empirical consumption model:

$$d\ln C_{i1} = \alpha_{01} + \alpha_{11} h_{i0} + \alpha_{21} dh_{i1} + X_i \alpha_{31} + e_{1i} \tag{1.23}$$

$$d\ln C_{i1} = \alpha_{02} + \alpha_{12} h_{i0} + \alpha_{22} H_i + X_i \alpha_{32} + e_{2i}. \tag{1.24}$$

The X_i vector includes variables that can indicate individual-specific preferences or changes in preferences. These variables are age, gender, having children, dummies of being diagnosed with chronic diseases since the first wave[12], ADL limitation and first differenced binary indicator of depression, becoming single, quitting employment, and country dummies as controls for preferences and country-specific factors in consumption expenditures. I include the death of the father and the mother also as explanatory variables since such an event is likely to influence the consumption expenditures e.g. through bequests or through the costs associated with the funeral. The first differenced logarithmic income is also included in X_i, allowing income shocks to influence consumption expenditures. I estimate two versions of the model: first, only the hazard indicators are included as regressors, second, the additional controls (vector X_i) are also included in the model.

The subjective survival probability is measured with error, which is also reflected by the large fraction of focal responses. As a consequence, the hazard level (h_{i0}), the differenced hazard (dh_{i1}) and the binary indicator of increasing hazard (H_i) are also measured with error. If the measurement errors in the differenced hazard and first wave hazard are correlated with the observed hazard values then the OLS estimator is biased. This is likely to be the case since negative measurement error can cause low observed hazard rates, therefore the differenced observed hazard and its measurement error are also correlated. In addition, OLS estimation can be biased due to unobservables. Unobserved changes in the health status can affect not only the consumption dynamics but also the reported survival probability, making the first differenced hazard endogenous in the model. These endogeneity concerns call for the application of the method of instrumental variables. The IV estimator is consistent only if the instruments are independent from the error term in the consumption model written up on the observed

[12] The following seven diseases are considered: heart attack, stroke, cancer, hip fracture, high blood pressure, high blood cholesterol, diabetes.

variables. This requirement is problematic if the measurement error is not of the classical type, i.e. it is correlated with the true hazard rates, which can be due to rounding. In the following I make the simplifying assumption that the instruments used (indicators of a sibling's death) are independent from the measurement errors in the hazard indicators.

1.4.2. First stage results

The death of a sibling between the two survey waves is used as instrument for the first differenced hazard and for the binary indicator of increasing hazard. Some details on this indicator is given in section 1.3.2. Hamermesh (1985) already pointed out the strong reliance of subjective survival probability on forebears' longevity. However, there are multiple reasons why I use only the death of a sibling as an instrument of changing mortality hazard. Firstly, it affects the subjective hazard and can be a valid instrument, as the death of a sibling is unlikely to have direct effect on food consumption expenditures. The latter might not be true for the parents or the children of the respondent. Secondly, the respondents are aged 50 or above, for whom the death of a parent is likely to affect the subjective mortality hazard to a less extent than for younger individuals. Including irrelevant instruments would exacerbate the problem of weak instruments. Table 1.2 indeed shows that the effect of the death of a parent on the differenced hazard is insignificant and smaller than the effect of the death of a sibling.

The level of first wave hazard is instrumented by a binary variable which equals one if the respondent has no siblings alive in wave one, but reports that he had siblings before. Section 1.3.2 provides some details on this indicator and on its effect on the reported hazard. Bloom et al. (2006) apply a different instrumenting strategy: they instrument the subjective survival probability with the age or age of death of the parents, using the HRS data. If a parent died at young ages then that might influence the further consumption path of the child. Also the parents and their children might share some consumption expenditures, and their age or age at death is more likely to directly affect the consumption expenditures, thus might not be valid instrument in the consumption model. Nevertheless, I make a robustness check in section 1.6.2 with respect to this alternative instrumenting strategy. Using binary instruments does not violate the consistency of the IV estimator. Both the probability of the death of a sibling and the joint probability of increasing hazard and sibling's death can be assumed to be constant as the sample size increases. Thus these probabilities do not converge to zero or to one with increasing sample size.

In Table 1.3 I present the coefficients of the instruments from the first stage of the consumption model. This table refers to the specification under equation (1.23), where the differenced hazard is a regressor. There are four specifications according to the inclusion of the additional controls (X vector), and to the estimation sample. First I estimate the model for the whole population aged at least 50 but not more than 80, then I restrict this estimation sample to those who have positive wealth holdings, according to the net worth indicator. Since the probability of the death of a sibling increases with the respondent's age, and age can have direct effect on

consumption decisions due to cohort specific consumption dynamics, I control for age under all specifications. I present also the value of the F-test, where the null hypothesis is that the two instruments are jointly insignificant.

ONLY AGE AS CONTROL

	Whole sample		Positive W	
	wave 1 hazard	diff. hazard	wave 1 hazard	diff. hazard
all siblings dead	0.009***	-0.004	0.009***	-0.005
	[3.51]	[1.36]	[3.66]	[1.48]
sibling dies	-0.000	0.008***	-0.000	0.008***
	[0.12]	[3.28]	[0.16]	[3.23]
F	6.23	6.41	6.78	6.42
Observations		13,350		12,647

WITH CONTROLS

	Whole sample		Positive W	
	wave 1 hazard	diff. hazard	wave 1 hazard	diff. hazard
all siblings dead	0.008***	-0.004	0.009***	-0.004
	[3.24]	[1.33]	[3.38]	[1.43]
sibling dies	0.001	0.007***	0.001	0.007***
	[0.54]	[3.00]	[0.46]	[2.95]
F	5.30	5.52	5.73	5.51
Observations		13,323		12,529

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.3: First stage estimation results, differenced hazard as regressor in the consumption model

Table 1.4 is analogous to Table 1.3, the difference is that Table 1.4 presents the selected first stage coefficients from the model of equation (1.24). Here the binary indicator of increasing hazard is included in the consumption model.

The results show that under all specifications the death of a sibling between the two survey waves increases the subjective hazard, and the subjective hazard in the first wave is significantly higher if all the siblings of the respondent have died by that time. The magnitude and the significance of these effects are not affected by restricting the sample to the wealthy individuals. On the other hand, the instruments are weaker if additional controls are included in the consumption models. The F statistics indicate that the instruments are the strongest if the binary indicator of increasing hazard is used as regressor, but the additional control variables are not included in the model (upper part of Table 1.4). I return to the problem of weak instruments in section 1.6.2.

1.5. Second stage results

Estimating the consumption models of equations (1.23) and (1.24) can reveal how the consumption level is adjusted after hazard shocks. At the same time, the ex ante effect of subjective mortality hazard on the consumption dynamics is also estimated. If the presented life-cycle model is realistic than the effect of first wave hazard on differenced consumption is negative,

Only age as control

	Whole sample		Positive W	
	wave 1 hazard	hazard incr.	wave 1 hazard	hazard incr.
all siblings dead	0.009***	-0.003	0.010***	-0.003
	[3.49]	[0.15]	[3.73]	[0.16]
sibling dies	-0.000	0.072***	-0.000	0.066***
	[0.02]	[5.22]	[0.21]	[4.66]
F	6.11	13.80	7.06	11.01
Observations		13,715		12,973

With controls

	Whole sample		Positive W	
	wave 1 hazard	hazard incr.	wave 1 hazard	hazard incr.
all siblings dead	0.008***	-0.003	0.009***	-0.003
	[3.15]	[0.14]	[3.39]	[0.16]
sibling dies	0.001	0.062***	0.000	0.057***
	[0.47]	[4.47]	[0.31]	[3.98]
F	4.99	10.10	5.75	8.04
Observations		13,582		12,850

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.4: First stage estimation results, increasing hazard indicator as regressor in the consumption model

whereas the effect of the indicator of increasing hazard is positive. A related model of consumption level is estimated by Skinner (1985b). Using cross sectional data from the Consumption and Expenditure Survey and using race- and occupation-specific life tables, he regresses the logarithmic consumption on the logarithm of mortality rate. Skinner estimates positive effect of mortality on consumption.

As discussed under the first stage results, I estimate the model on the whole applicable sample and also on the sample of individuals with positive wealth holdings. The theory predicts that the consumption expenditures of wealthy individuals are more responsive to the hazard shocks. I also reestimate the models with including control variables in addition to age, which might affect the consumption dynamics. Due to the measurement error in the hazard indicators and to the potential influence of unobservables, I apply the method of IV estimation with the death of a sibling between the two waves, and the death of all siblings before wave one as instruments. However, for the sake of comparison I also reestimate the models with OLS.

The models are estimated for individuals aged between 50 and 80, but in section 1.6.1 I analyze the robustness of the results with respect to including the oldest respondents in the estimation sample. Zero reported survival probabilities are excluded from the estimations. All the households, and not only the single households are included in the estimation sample. Although the modelling assumption that consumption expenditures are based on individual decisions can be more reliable for single individuals, restricting the sample to singles would necessitate the exclusion of almost 80% of the observations and thus small sample problems would arise.

In the first set of specifications I include the differenced hazard as a measure of increasing hazard (equation 1.23)). The estimated coefficients of interest are presented in Table 1.5, the

full set of the estimated coefficients if additional controls are included are reported in Appendix 1.A.1. The estimations are repeated with the difference that not the change in hazard is included as a regressor, but a dummy variable indicating if a big increase is recorded in the subjective mortality hazard (equation (1.24)). The increase in hazard is defined to be big if there is at least 1.5 percentage points decrease in the adjusted two-year survival probability between the two waves. The binary variable is zero if no such decrease is recorded, but the survival probability is not missing. The estimated coefficients based on this specification are reported in Table 1.6, the detailed estimation results are reported in Appendix 1.A.2.

No controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
diff. hazard	2.785	-0.150	4.847**	-0.157
	[1.20]	[1.09]	[2.09]	[1.11]
wave 1 hazard	-0.962	-0.526**	-0.848	-0.541**
	[0.88]	[2.39]	[0.71]	[2.41]
Observations		13,350		12,647

Only age as control

	Whole sample		Positive W	
	IV	OLS	IV	OLS
diff. hazard	2.503	-0.136	4.669*	-0.147
	[0.97]	[1.00]	[1.80]	[1.06]
wave 1 hazard	-1.548	-0.489**	-1.194	-0.516**
	[0.47]	[2.02]	[0.34]	[2.08]
Observations		13,350		12,647

With controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
diff. hazard	3.060	-0.137	5.248*	-0.156
	[1.11]	[1.02]	[1.86]	[1.14]
wave 1 hazard	-1.870	-0.461*	-1.541	-0.482*
	[0.52]	[1.89]	[0.41]	[1.91]
Observations		13,223		12,529

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.5: Consumption model estimation results, differenced hazard as regressor

If the differenced hazard is included as regressor in the consumption model (Table 1.5) then the expected positive effect of this indicator cannot be seen based on the OLS estimates. On the other hand, the effect of the first wave hazard is significantly negative only under the OLS specifications. This effect is still negative, but insignificant under the IV models. Based on the IV estimation results, the partial effect of the differenced hazard on consumption expenditures is positive, but this effect is significant at 10% significance level only for those who are not credit constrained. This is in line with what the life cycle model predicts: if someone lives from annuity type income then the consumption is unaffected by the subjective mortality hazard. These results suggest that the ex post effect of subjective hazard on consumption expenditures is stronger than the ex ante effect of subjective hazard.

Controlling for the socioeconomic indicators, the instruments are considered to be exogenous. Omitting other control variables causes bias in the IV estimates if those are related to the instrument. This can be a concern in case of the age indicator: since the siblings are often of similar age, the age of the respondent is positively correlated with the probability that a sibling dies. Therefore I include age as regressor under the preferred specifications. If age is not included as regressor then the estimated coefficients of differenced hazard and increasing hazard are significant at 5% significance level. The presented results also show that the estimated effects of the hazard measures are robust to the inclusion of the additional control variables.

No controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
hazard incr.	0.277	-0.011	0.513**	-0.002
	[1.11]	[0.86]	[2.00]	[0.18]
wave 1 hazard	-2.683	-0.406**	-3.658**	-0.408**
	[1.60]	[2.11]	[2.07]	[2.07]
Observations		13,715		12,973

Only age as control

	Whole sample		Positive W	
	IV	OLS	IV	OLS
hazard incr.	0.211	-0.007	0.446	0.002
	[0.76]	[0.51]	[1.51]	[0.15]
wave 1 hazard	-3.695	-0.334	-4.439	-0.342
	[1.08]	[1.56]	[1.31]	[1.54]
Observations		13,715		12,973

With controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
hazard incr.	0.305	-0.007	0.571	-0.001
	[0.90]	[0.58]	[1.55]	[0.05]
wave 1 hazard	-4.401	-0.298	-5.188	-0.299
	[1.13]	[1.38]	[1.33]	[1.32]
Observations		13,582		12,850

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.6: Consumption model estimation results, increasing hazard as regressor

According to the implications of the life-cycle model, increasing mortality hazard indicated by a drop in the survival probability should lead to increased consumption expenditures. The estimation results show the expected sign of this effect if the indicator of increasing hazard is instrumented, but the effect is significant only if age is not controlled for, and those with zero wealth holdings are excluded (Table 1.6). On the other hand, the coefficient of the first wave hazard is negative both under the OLS and IV estimates, but its magnitude is sensitive to the estimation method. Based on the CRRA utility function, the coefficient of the first wave hazard is the negative of the inverse of the coefficient of relative risk aversion. The OLS estimates indicate a much higher risk aversion coefficient (around $2-3$) than the IV estimates do (around $0.2-0.3$).

Based on the presented results it is clear that using instrumental variables when estimating the effect of subjective hazard on consumption is important. It affects not only the size of the estimated coefficients but in some cases also the sign of those. The absolute value of the IV estimates are always above the OLS estimates. The preferred specifications are the ones without the inclusion of additional controls apart from age, estimated with IV method on the subsample of individuals with positive wealth. These specifications indicate that the consumption path is influenced by the hazard shocks, although this influencing effect is weakly significant.[13] The positive sign of this effect correspond to the predictions of the life-cycle model. The coefficient of the first wave hazard is sensitive to the included indicator of changing hazard. There is strong negative correlation between the first wave hazard and the differenced hazard (the correlation coefficient is -0.45), which can increase the sensitivity of the coefficient estimates, and also the problem of weak instruments is exacerbated by it. On the other hand, the correlation coefficient between the first wave hazard and the binary indicator of increasing hazard is weaker (-0.1), therefore the estimation results are more reliable if the binary indicator is included in the model. However, it might be that in this specification the negative coefficient of the first wave hazard is due to the positive effect of differenced hazard, which cannot be fully captured by the binary indicator of increasing hazard.

The magnitude of the estimated effect of a hazard shock is not negligible. Based on the logarithmic transformation, increasing the mortality hazard by one is equivalent to decreasing the two-year survival probability for example from 80% to 30% or from 50% to 20%. Such a change in mortality hazard is estimated to have around ten times larger effect on the consumption expenditures than a 1.5 percentage points or higher decrease in the two-year survival probability. The estimated positive partial effect of increasing hazard on logarithmic consumption is around the standard deviation of the logarithmic consumption level. The effects are nonlinear. Around the median expenditure, if the logarithmic value of food consumption expenditures decreases or increases by 0.5 due to a shock in mortality hazard then that is equivalent to $80 - 140$ EUR change in the individual monthly food expenditures.[14]

For a 60 year old man a 1.5 percentage points decrease in the two-year survival probability is approximately equivalent to 4 years decrease in the expected remaining lifetime (from 21 years to 17 years), and to 0.02 increase in the two-year subjective hazard.[15] Based on the results presented in the middle part of Table 1.5, such a decrease in the expected longevity leads to around 190 EUR increase in the annual expenditure on food at the median, ceteris paribus, if the wealth holdings are not zero. The model extended with additional controls predict a higher

[13] As indicated in section 1.3.1, these results are based on the mean of the five imputed consuption, income, and wealth measures. Reestimating the preferred specifications separately on the five imputed datasets shows that the estimated coefficient of the differenced hazard is between 3.788 and 4.986, and that of the binary indicator of increasing hazard is between 0.340 and 0.499.

[14] The mean of the differenced hazard in the estimating sample is 0.007, and the median is 0.001. Thus on average the predicted ceteris paribus increase in consumption expenditures due to the changing hazard is moderate, based on the estimation results presented in Table 1.5.

[15] These calculations are based on the German life table. It is assumed that before the hazard shock the subjective survival probability of this individual was equal to the life table survival probability.

increasing effect, around 220 EUR.[16]

1.5.1. Euler equation

The standard approach in the empirical analysis of consumption is estimating the Euler equation based on the life-cycle model of consumption. An overview of this approach is provided by Attanasio and Weber (2010). Estimating the Euler equation makes possible to test the validity of the life-cycle model, and to estimate the parameters of the utility function. Although in this chapter my focus is on the effect of mortality hazard shocks on consumption expenditures, I present here the results of the Euler equation estimation. Since both the differenced hazard and the binary indicator of increasing hazard are correlated with the first wave hazard, including only the first wave hazard as regressor leads to omitted variable bias. Instrumenting the first wave hazard with the indicator of the death of all siblings before wave one does not solve this problem because this instrument is also a predictor of the changing hazard (as presented in Tables 1.3 and 1.4), so the ex ante effect of subjective hazard cannot be separately identified. Nevertheless, the Euler equation estimation results can be compared to the estimation results presented in section 1.5.

The life-cycle model implies that the expected growth rate of consumption expenditures is lower if the current mortality hazard is higher. This implication can be tested by estimating the following equation:

$$d \ln C_{i1} = \alpha_0 + \alpha_1 h_{i0} + X_i \alpha_2 + e_i. \tag{1.25}$$

This model is analogous to equations (1.23) and (1.24), but the differenced hazard or the indicator of increasing hazard is excluded. The adjusted subjective cumulative hazard of dying in the next two years at wave one is used as regressor (h_{i0}). The X_i vector includes the same variables as earlier. Again, I apply both IV and OLS estimation methods. Instrumenting is needed because of the likely presence of measurement error and unobserved variables. The instrument is the binary indicator which equals one if the respondent had siblings but none of the siblings are alive in wave one. The model is estimated with and without the inclusion of the additional control variables, and on two samples: the whole estimation sample and the sample of individuals with positive wealth holdings. The estimated coefficients of the first wave hazard indicator are reported in Table 1.7.

Based on the Euler equation, the presented coefficients equal the negative inverse of the coefficient of relative risk aversion (i.e. the negative intertemporal elasticity of substitution). However, reliable estimation of the parameter of the utility function would require longer time-series than two years. Nevertheless, the results show that the estimated effect of subjective mortality hazard on consumption expenditure dynamics is negative both under the OLS and IV

[16] These estimates are average effects. The life-cycle model (equation (1.17)) implies that the true effect of changing hazard is heterogeneous, and depends on the initial hazard. As I have only two instruments in the empirical model, and the interaction of these instruments equals zero by definition, it is not possible to interact the differenced hazard with the initial hazard under my IV approach. Lochner and Moretti (2011) show that under such circumstances the estimated single effect is a weighted average of the true heterogeneous effects, but the weights under the IV estimation are different from the weights under the OLS estimation.

Only age as control

	Whole sample		Positive W	
	IV	OLS	IV	OLS
wave 1 hazard	-3.579	-0.317	-4.902	-0.330
	[1.13]	[1.59]	[1.58]	[1.61]
Observations		14,468		13,677

With controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
wave 1 hazard	-4.470	-0.246	-5.929	-0.265
	[1.20]	[1.21]	[1.60]	[1.25]
Observations		14,220		13,448

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.7: Euler equation estimation results

estimations, but the estimated effect is insignificant. This effect is larger in absolute value under the IV estimations. The negative estimated effect is in line with the predictions of the life-cycle model.

Again, the coefficients of interest change moderately with the inclusion of additional controls. If additional controls are included then the hazard coefficient becomes larger in absolute value under the IV estimation. The estimated coefficients indicate that the effect of the lagged value of subjective hazard on the differenced consumption is weaker for those who have no wealth holdings. This is also in line with the life-cycle model, since if the credit constraint is binding then the Euler equation does not hold.

The estimated effect of the first wave hazard is comparable to the estimates if the binary indicator of increasing hazard is included in the model (Table 1.6). On the other hand, these results are different from the results of the consumption model with the differenced hazard included. Using the observed consumption growth as dependent variable, the Euler equation estimates suffer from omitted variable bias. The differenced hazard also influences ex post the differenced consumption, and the differenced hazard is negatively correlated with the first wave hazard.

1.5.2. Endogeneity concerns

The validity of the instrumenting strategy is violated if the death of a sibling has direct effect on the consumption expenditures. In the reduced form model the death of a sibling between the two waves and the death of all the siblings before wave one influence the consumption expenditures. If a sibling dies between the two waves then the consumption expenditures increase, and if none of the siblings are alive at wave one then the second wave expenditures are smaller relative to the first wave expenditures. I assume that this influencing mechanism works through the effect on the subjective mortality hazard. However, the death of a sibling can have direct effect on the expenditures if the deceased sibling was a member of the respondent's household at the time of the first observation or if the respondent received bequest from the deceased sibling.

Consumption is measured as household level expenditure on food divided by the household size. This measure might be directly affected by the death of the sibling living in the household if the expenditure is a nonlinear function of the household size. Because of this concern I reestimate the consumption models with excluding from the estimation sample the respondents whose deceased sibling was a household member in the first wave. This information is not directly included in the data, but two indicators can be used for this purpose. First, I exclude those individuals for whom the household size changed between the two waves (18% of the sample). Second, I exclude those who report that a sibling is a household member either in the first or the second wave (1% of the sample). The problem with the second restriction is that the relation of the household members to the respondent is unambiguous only for the so-called household respondent, and not for the spouse.

I also reestimate the models with excluding those individuals who report receiving gift or inheritance of 5 thousand Euro or more since the first wave, and for whom it can be identified that it was received from a sibling (less than 0.5% of the sample). With this restriction it can be analyzed if inheritance from the deceased sibling drives the estimation results.

I include age as control variables in these estimations, and use only the sample of the individuals with positive wealth holdings. None of these restrictions influence the estimated sign of the indicators of changing subjective hazard, and the size of the estimated effect is qualitatively unaffected. The coefficient of the first differenced hazard remains significant at 10% significance level if those respondents are excluded whose sibling was a household member or who received bequest from a sibling. These results indicate that the positive effect of a hazard shock on consumption expenditures is not driven by a direct influence of the death of the sibling on the consumption expenditures. The coefficient of the first wave hazard is also robust to these restrictions.

If the consumption preferences change after the death of a sibling then that can also violate the exogeneity of the instrument. The marginal utility of overall (food) consumption, and also of the different consumption categories might change after a hazard shock.[17] Based on the risk preference questions included in the Health and Retirement Study questionnaire, Barsky et al. (1997) document that the preference parameters of individuals aged 50+ are indeed heterogenous. In addition, Elder (2007) finds some evidence that subjective longevity increases the risk tolerance of the HRS respondents. Finkelstein et al. (2008) provide evidence that the marginal utility of consumption increases with health.

In this chapter consumption is measured by the expenditure on food consumed at and away from home. If the two categories of food expenditures are adjusted differently after the hazard shock then that can indicate that the preferences change either with the death of a sibling or with the hazard shock. The first scenario implies that the instrument has direct effect on the

[17] There are two different cases. First, if the marginal utility of consumption increases with subjective survival probability then the positive effect of the upward hazard shock becomes smaller. Second, if the marginal rate of substitution between two consumption categories depends on the subjective survival probability then the consumption structure changes after a hazard shock.

consumption expenditures. However, the second scenario implies that the preferences are state dependent, and the utility function specified in section 1.2 is simplistic.

For the sake of analyzing how the preferences change after the death of a sibling I reestimate the consumption model with using the expenditure on food consumed at home as consumption measure, and separately I also analyze the adjustment of expenditure on food consumed away from home. The average share of expenditures on food consumed at home within the total food expenditures is 88% in the sample of people aged $50-80$ (the median is 91%). Table 1.8 presents the estimated hazard coefficients if the differenced logarithmic value of expenditure on food consumed at home is the dependent variable. In these models I again include age as control variable, and the IV estimation is applied. The estimated coefficients of the differenced hazard and increasing hazard indicators are similar in magnitude to the respective coefficients if the overall expenditure on food is used as consumption measure (Tables 1.5 and 1.6). The expenditure on food consumed at home is estimated to be adjusted upwards after the hazard shock more than the total expenditure. This finding indicates that the adjustment takes place through this category of expenditures, and not through the expenditures on food consumed away from home.

Differenced hazard as regressor

	Whole sample	Positive W
diff. hazard	3.861	6.242**
	[1.49]	[2.32]
wave 1 hazard	0.717	1.400
	[0.22]	[0.40]
Observations	13,421	12,709

Increasing hazard indicator as regressor

	Whole sample	Positive W
hazard incr.	0.386	0.684**
	[1.43]	[2.34]
wave 1 hazard	-1.693	-2.286
	[0.49]	[0.66]
Observations	13,786	13,035

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.8: IV estimation results, differenced logarithmic expenditure on food consumed at home as dependent variable

In both waves for around 60% of the respondents the amount spent on food away from home is zero. It can be analyzed how the propensity to consume food away from home is affected by a shock in the subjective hazard. I estimate the following bivariate probit model, written up on latent variables which are denoted with stars:

$$\begin{aligned} pos\_wave2_i^* &= \theta_{10} + \theta_{11} H_i + \theta_{12} age_i + w_{1i} \\ H_i^* &= \theta_{20} + \theta_{21} sibl\_die_i + w_{2i}, \end{aligned} \tag{1.26}$$

where pos_wave2_i is the binary indicator of positive expenditures on food consumed away from

home in wave two, H_i is the binary indicator of an at least 1.5 percentage points decrease in the subjective survival probability, and age_i is the age of the respondent at the second survey wave. Estimating this bivariate probit model can handle the potential endogeneity of the hazard indicator in the model of food expenditures. However, if the death of a sibling has direct effect on the probability of consumption away from home then this simple model can not distinguish the direct and indirect effects. The model is estimated separately for those who report positive and zero expenditures in the first wave. The estimated coefficients of increasing hazard are reported in Table 1.9.

Positive expenditure in wave 1	
hazard incr.	-0.857**
	[2.29]
Observations	4,285
Zero expenditure in wave 1	
hazard incr.	0.072
	[0.06]
Observations	9,284

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.9: Estimated coefficient of increasing hazard in the model of reporting positive expenditures on food consumed away from home in wave 2

These estimates indicate that consuming food away from home becomes less likely after a shock in the subjective hazard, which is considered as an evidence for changing preferences. This effect is significant only for those who report positive expenditures at wave one. These results provide some evidence that after the hazard shock, food consumed away from home might be substituted with consumption at home.

To conclude, the estimated positive effect of an upward hazard shock on consumption expenditures is driven by the effect on the expenditures on food consumed at home. The results indicate that the preferences might be state dependent, but based on these finding it cannot be decided whether the death of a sibling has a direct effect on the preferences or it has only indirect effect through the changing subjective hazard. Nevertheless, these results do not contradict the finding of section 1.5 that the total consumption expenditures are adjusted upwards as a consequence of the increasing subjective hazard.

1.5.3. Selectivity

If the sample is nonrandom then that can potentially cause bias in the estimated coefficients. Only those individuals are included in the estimations for whom both wave 1 and 2 observations are available. In addition, the indicator of subjective survival probability can not be missing. As documented by Borsch-Supan et al. (2008), the attrition rate between the first two waves of the survey is 31.7%. The majority of the attrition is not due to death, only 2.6% of wave one respondents deceased between the two waves. Taking into account the item non-response to the subjective survival probability question, only 58% of the age-eligible wave one respondents can

be included in the estimation sample.

Attrition is more likely for individuals with higher subjective mortality hazard in the first wave of the sample. The earlier death of siblings has no significant effect on the probability of attrition, but the number of siblings alive has significantly negative effect on that. This indicates that the death of a sibling might also be related to the inclusion in the sample. In addition, the willingness to respond in the first wave is a strong predictor of attrition.

The nonresponse rate to subjective survival probability in the sample is relatively high, around 8%. The item nonresponse rate varies across the countries, it is the highest in France (18%) and Spain (16%), lowest in Germany (4%), based on both waves of the survey, excluding the respondents aged above 80. Low propensity to report subjective survival probability can indicate that measurement errors are high in the observed survival probability and hazard indicators, provided that the reasons for the high nonresponse rate are some difficulties in answering the question about survival probability. The probit model of item nonresponse indicates that the probability of not answering the survival probability question is higher for those who are older and who report worse health status.[18]

If the selection into the sample is related to the instruments used in the consumption model, and if the consumption dynamics are systematically different between the included and missing observations then the IV estimates are biased. Observations on the consumption decisions near the end of life are likely to be missing. The effect of increasing mortality hazard indicator can be underestimated if consumption becomes more responsive to the hazard near the end of life. This can be the case if the uncertainty in survival probability decreases with approaching the end of life. On the other hand, the effects are overestimated if the marginal utility of consumption approaches zero before death.

The estimated effect of an upward hazard shock is stronger if the first wave hazard was above the median two-year hazard (i.e. above 0.02). This result suggests that the overall effect of a hazard shock is likely to be underestimated due to the attrition and to the higher item nonresponse rate among respondents with higher first wave mortality hazard.

1.6. Robustness and specification checks

1.6.1. Estimation sample

In the following robustness and specification checks only the hazard measures and age are included in the consumption models, the sample is restricted to individuals with positive wealth holdings, and only the IV estimates are analyzed. As the first robustness check, I reestimate the models with including in the sample those who are aged above 80 but not more than 90.

[18] A probit model of item nonresponse is estimated, where the indicator of noresponse is set to one if life expectancy is not reported either in the first or second wave, thus for whom the differenced survival probability is missing. The control variables besides the country dummies are the age, gender, marital status, education level, income, and self reported health status of the respondents. I also control for the interviewer's observation of declining willingness to answer during the interview. This is reasonable since the expectation questions are in the final block of the SHARE questionnaire, and by that time the respondents can become less willing to respond.

In this estimation sample the oldest 1% is still excluded, for whom the item nonresponse rate to the survival probability question is around 30%, which indicates that for the very old the consumption model cannot provide reliable estimates. Since the influential role of subjective mortality hazard on the consumption expenditure decisions of individuals aged above 80 might be moderate and the reported survival probabilities are less reliable, in the basic estimations I exclude them from the sample.

In Table 1.10 I present the results of the IV estimations where age is controlled for. The first rows under both blocks include the reference results from section 1.5. The magnitude of the estimated coefficients are strongly affected by the age restriction of the sample, but the estimated negative effect of the first wave hazard is robust. The first wave hazard is estimated to have stronger and negative effect on the consumption path of the oldest individuals, provided that the differenced hazard is included in the model. On the other hand, the effect of increasing hazard becomes insignificant and close to zero if the individuals aged between $81-90$ are also included in the sample. One explanation for the sensitivity of the coefficients is the different explanatory power of the instruments in the two samples: the effect of the death of all siblings on the first wave hazard indicator becomes stronger, whereas the effect of the death of a sibling on the hazard shock indicators become weaker with the inclusion of the oldest respondents. A second explanation can be that people aged above 80 are less likely to adjust their consumption expenditures after an upward shock in the subjective hazard, which is reflected by the insignificant and small coefficients of the indicators of changing hazard.

First differenced and increasing hazard coefficients

	diff. hazard coefficient	hazard incr. coefficient
2SLS	4.669*	0.446
	[1.80]	[1.51]
2SLS, 80+ included	0.605	0.061
	[0.62]	[0.13]
2SLS, 0% probability included	2.953*	0.633*
	[1.72]	[1.77]
2SLS, pos. financial wealth	4.915*	0.497
	[1.66]	[1.20]

First wave hazard coefficients

	diff. hazard as regressor	hazard incr. as regressor
2SLS	-1.194	-4.439
	[0.34]	[1.31]
2SLS, 80+ included	-2.240	-4.561
	[0.81]	[1.47]
2SLS, 0% probability included	-1.496	-2.861
	[0.60]	[1.09]
2SLS, pos. financial wealth	-1.921	-5.029
	[0.54]	[1.40]

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.10: Robustness checks with respect to the estimation sample: hazard indicator coefficients in the consumption models (IV estimation)

In the benchmark specifications the hazard indicators are missing if the reported survival

probability is zero, which holds for around 5% of the estimation sample. Reporting zero survival probability is more likely for individuals with some health problems, and for older, single individuals. This implies that due to rounding error the zero reported probability might correspond to very low but nonzero true subjective survival probability. I reestimate the models using the assumption that the reported zero probability corresponds to 0.5% survival probability to the target age, based on which assumption the subjective hazard indicator can be calculated. The sign of the estimated adjustment after a hazard shock is unaffected by this modification. The estimated effect of the differenced hazard becomes weaker, whereas that of the binary indicator of increasing hazard becomes stronger. The first wave hazard coefficients remain insignificant and negative. These findings suggest that the observed zero survival probabilities are due to measurement error, potentially due to rounding to zero from a small probability, to which the differenced hazard measure is more sensitive than the binary indicator of increasing hazard.

In the third robustness check I repeat the benchmark specification with the difference that the individuals with positive wealth are selected not based on the net worth but on the financial wealth measure. If non-financial wealth is illiquid and cannot be used for financing consumption needs then the credit constraint can become binding also for those who report positive net worth but zero financial wealth holdings. 80% of the individuals in the sample have positive financial wealth holdings in both waves. The coefficients reported in Table 1.10 indicate that the effect of a hazard shock on consumption expenditures is qualitatively robust to the choice of wealth category. The estimated ex ante end ex post effects of subjective hazard are stronger for individuals with positive financial wealth. The signs of the estimated effects are in line with the predictions of the life-cycle model. However, the estimated coefficients are only weakly significant.

The presented checks indicate that it is a robust finding that consumption expenditures are adjusted upwards if the subjective hazard increases. This adjustment is weaker for the oldest individuals. The negative coefficient of the first wave hazard is also a robust finding.

1.6.2. Instrumental variables methods

This set of specification checks is with respect to the applied method of instrumental variables. The consumption models are exactly identified since only two instruments are used in the models and there are two endogenous variables. Therefore the two-stage least squares and limited information maximum likelihood estimations are identical. However, since there is some evidence that the instruments are weak,[19] it is reasonable to compare the results with alternative estimators. Weak instruments can cause large bias in the finite sample two-stage least squares estimates. Hahn et al. (2004) suggest the usage of Fuller's estimator (which is a modified LIML

[19] The Stock-Yogo critical values reported after the *ivreg2* command in Stata indicate that the problem of weak instruments is present in the estimated consumption models, especially if the differenced hazard is included in the model. The values of the Kleinbergen-Paap rk F-statistic lie between $5-10$, depending on the specification, with smaller values if additional regressors are included in the models.

estimator) with parameters 1 or 4.[20] An alternative can be the jackknife instrumental variables estimator (JIVE), which can mitigate the finite-sample bias of the 2SLS estimator. I consider two alternatives: the method suggested by Angrist et al. (1999) where the jackknife first stage fitted value is used as instrument in the second stage IV estimation (JIVE1), and the method suggested by Blomquist and Dahlberg (1999) where the jackknife first stage fitted value is used as a regressor in the second stage OLS estimation (JIVE2).[21] These results are presented in Table 1.11, where the benchmark 2SLS estimates are also presented. Again, only the results for individuals with positive wealth holdings are analyzed.

First differenced and increasing hazard coefficients

	diff. hazard coefficient	hazard incr. coefficient
2SLS	4.669*	0.446
	[1.80]	[1.51]
Fuller(1)	4.489*	0.430
	[1.82]	[1.52]
Fuller(4)	4.023*	0.388
	[1.88]	[1.56]
JIVE1	6.095*	0.530
	[1.73]	[1.42]
JIVE2	4.666	0.446
	[1.52]	[0.51]

First wave hazard coefficients

	diff. hazard as regressor	hazard incr. as regressor
2SLS	-1.194	-4.439
	[0.34]	[1.31]
Fuller(1)	-1.156	-4.284
	[0.35]	[1.33]
Fuller(4)	-1.062	-3.883
	[0.36]	[1.37]
JIVE1	-1.492	-5.585
	[0.32]	[1.43]
JIVE2	-1.139	-4.391
	[0.28]	[0.51]

Absolute value of t statistics in brackets (cluster robust under 2SLS, LIML and Fuller estimates)
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.11: Specification checks with respect to the IV estimation method: hazard indicator coefficients in the consumption models

The estimated sign and significance of the hazard indicators are robust to the alternative estimation methods. It is a robust finding that the estimated effect of increasing hazard is positive on consumption expenditures. Except for the JIVE2 method, this effect is significant at

[20] Fuller's estimator is a member of the k-class estimators. If the structural model is $Y = X\beta + u$, then the k-class estimator is $\hat{\beta} = (X'(I - kM_Z)X)^{-1} X'(I - kM_Z)Y$. Here Z is the vector of first stage regressors, and $M_Z = I - P_Z = I - Z(Z'Z)^{-1} Z'$. The OLS estimator is obtained if $k = 0$, the 2SLS is obtained if $k = 1$. The LIML estimator is obtained if $k = \lambda$, where λ is the smallest eigenvalue of the matrix $W'P_Z W(W'M_Z W)^{-1}$ with $W = [Y, X]$.

For Fuller's estimator $k = \lambda - \frac{a}{N-K}$, where N is the number of observations, and K is the number of regressors in the first-stage model. If $a = 1$ then the model is approximately unbiased, if $a = 4$ then there is bias, but the mean squared error is smaller. Further details about these estimation methods are provided by Davidson and MacKinnon (1993) and Hahn et al. (2004).

[21] The *jive* command of Stata written by Poi (2006) is applied in the jackknife estimations.

In his Monte Carlo simulations Poi (2006) reports cases where the two types of JIVE results give considerably different estimates. In addition, both Hahn et al. (2004) and Davidson and MacKinnon (2006) caution against using the jackknife IV estimators based on the bias, dispersion, and reliability of the estimates.

10% if the first differenced hazard is used as regressor. The effect of the hazard shock is estimated to be stronger if the jackknife instrumental variables estimator suggested by Angrist et al. (1999) is used. The point estimates of the Blomquist and Dahlberg (1999) type estimation are close to the benchmark two-stage least squares estimates. The results also reinforce that the ex ante effect of subjective hazard on the consumption path is negative. However, this effect is insignificant under all specifications.

It can be concluded that the adjustment of consumption expenditures after a hazard shock can be reliably estimated by the preferred 2SLS estimation method. Increasing subjective mortality hazard is estimated to have positive effect on consumption expenditures. These results change only slightly if Fuller's estimator or the jackknife instrumental variable methods are applied.

1.6.3. Extensions of the life-cycle model

The life-cycle consumption model derived in section 1.2 is based on the assumption that the decision makers have annuity income. The implications of the model might not hold if income is time varying. If the credit constraint is binding for an individual who expects increasing income then the expected consumption path can be positively sloped. This might hold especially for the younger respondents who are active in the labor market. The optimal consumption path is also modified if income is uncertain. If uncertainty is introduced to the life-cycle model then a modified Euler equation can be derived, following Carroll (2001):

$$E_t\left(\frac{C_{it+1}}{C_{it}}\right) = \left(E_t\left(I_{it+1}\right)\beta R\right)^{\frac{1}{\gamma}} V_i^{\frac{\gamma+1}{2}}, \tag{1.27}$$

where $V_i \geq 1$ is an individual-specific measure of income uncertainty. This expression implies that the planned consumption path becomes flatter or even positively sloped with income uncertainty, in which case the previously derived positive effect of increasing hazard might not hold. The intuition for this result is that income uncertainty necessitates precautionary savings, and consumption is postponed to later ages when the uncertain income is realized.

As an indicator of time varying income the employment status of the respondent is used. For the sake of simplification, the respondent is defined to be retired if he does not report employment or self employment in any of the two waves of questionnaire (64% of the respondent in the estimation sample). If the consumption models are estimated on the subsample of retired individuals then the IV estimates of the increasing hazard indicators become stronger, and the estimated positive effect is significant at 10% significance level. Excluding additional control variables apart from age, and estimating the model on the sample of those retired individuals who have positive wealth, the estimated coefficient of the differenced hazard becomes 5.75 (previously 4.67), and the coefficient of the dummy of increasing hazard becomes 0.55 (previously 0.45).

Thus the effect of increasing hazard on consumption expenditures is stronger for those who are not employed. At the same time, the estimated ex ante effect of mortality hazard on consumption path becomes also slightly stronger, it remains negative but insignificant.

The influencing effect of subjective mortality hazard on the consumption expenditures can also be weaker if the consumption decision is not an individual decision, but for example a joint decision of the household members. The presented life-cycle model assumes that the consumption is a result of the individual optimizing behavior. The model also assumes that there are no bequest motives. Although in two related papers Hurd (1989) and Gan et al. (2004) find using HRS data that bequest motives are weak, such motives can still have some influence on consumption decisions. If the life-cycle model is extended with bequest motive then the model can be solved only numerically. However, a closed form solution can be derived in a simple two-period model, which indicates that the partial effect of mortality hazard on the consumption level becomes smaller with bequest motives.[22]

The most reliable indicator of bequest motive is whether the respondent has children or not. It can be assumed that the bequest motives are weaker for those who do not have children. However, only 10% of the respondents fall into this category, and due to the small sample the consumption model coefficient estimates become imprecise with t statistics close to zero. The similar holds if the bequest motives and joint decisions are indicated by living in non single households. Restricting the sample to single households would necessitate the exclusion of 84% of the otherwise eligible observations.

Receiving social support from someone outside the household can also imply that the consumption expenditures do not result from individual decisions, and it can indicate bequest motives as well. Therefore, receiving social support can weaken the effect of subjective hazard on consumption expenditures. I define an individual to receive social support if he reports receiving personal care or practical household help from someone outside the household during the 12 months prior to the interview in any of the two waves.[23] 25% of the respondents included in the estimation sample have received such support in any of the two waves. The majority of the support is practical household help, and the help is typically provided by the children of the respondents (less than 10% of the help is received from a sibling). If the sample is restricted to those who do not receive social support then the positive effect of increasing hazard on consumption expenditures becomes stronger both if the differenced hazard and if the binary indicator of increasing hazard is used. Both indicators of hazard shock are significant at 5% significance level, with coefficients of 5.11 and 0.79, respectively.

It can be concluded that no empirical evidence could be found that bequest motives would significantly affect the influential role of subjective hazard on consumption expenditures. The results also suggest that joint decisions on consumption expenditures might weaken the estimated

[22] The following simplifying assumptions are made in the two-period life-cycle model. The utility of bequest has the same functional form as that of consumption, but multiplied with an individual-specific multiplicator (B_i). This term indicates the strength of the bequest motive. In the first period the individual decides on the current consumption level, and in the second period he either consumes all the remaining wealth (if survives) or leaves bequest (if dies).

Under this assumption it can be derived that the sign of the effect of subjective hazard on the optimal consumption level is the same as the sign of $(1 - B_i)$, provided that the credit constraint is not binding. Therefore the partial effect of mortality hazard is smaller if bequest motives are stronger.

[23] Due to the survey design, receiving financial transfers cannot be reliably included in this analysis. The survey asks only about receiving financial gift amounting 250 EUR or more. Only 5% of the respondents in the second wave report receiving such gift.

effect of a hazard shock on consumption decisions.

1.7. Concluding remarks

The life-cycle model with uncertain lifetime predicts that the effect of subjective mortality hazard on expected consumption dynamics is negative, whereas an upward shock in mortality hazard leads to higher consumption expenditures. These effects hold only for those individuals for whom the assumed credit constraint is not binding. The main novelty of this chapter is to identify the influencing role of changing hazard on consumption expenditures. The effects of the subjective hazard measures are identified by using the death of a sibling as instrument. Using the first two waves of the Survey of Health, Ageing and Retirement in Europe, the indicators of the death of a sibling between the two survey waves and before the first wave are used as instruments for the differenced hazard and first wave hazard indicators.

The empirical results confirm the implication of the life-cycle model about the effect of increasing mortality hazard. People aged $50-80$, who have positive wealth holdings are estimated to adjust their consumption expenditures after an upward hazard shock. The magnitude of this effect is not negligible, and the positive estimated effect of increasing mortality hazard on consumption expenditures is a robust result. The estimated effect is stronger if the employed individuals and those receiving personal care or practical household help are excluded from the sample. Consumption is measured with expenditure on food, and the results indicate that the upward adjustment after the hazard shock takes place through the adjustment of expenditures on food consumed at home. If the effect of increasing and decreasing subjective hazard on consumption expenditures is symmetric, then the estimation results also indicate that increasing expected longevity leads to smaller consumption expenditures, hence to slower wealth decumulation. The assumption of symmetric effects is reasonable for small changes in the expected lifetime. My results also confirm that survival probabilities reported by survey respondents contain economically relevant information about longevity expectations.

Some evidence is also found for the negative effect of first period mortality hazard on the consumption dynamics, which is implied by the Euler equation of the life-cycle model. However, this estimated ex ante effect is more sensitive to the empirical specifications than the estimated adjustment after the hazard shock. Estimating the Euler equation with neglecting the effect of changing hazard can lead to biased estimates since the initial hazard included in the Euler equation is correlated with the hazard shock, which is excluded from the Euler equation.

The limitations of the finding about the adjustment of consumption expenditures have to be kept in mind: it is based on only two observation years, and a selective European sample is used, thus the evidence for adjustment might not be valid in less developed countries. In addition, these results are based on a sample of elderly people, the effect of mortality hazard shocks on consumption expenditures is likely to be considerably different at younger ages.

1.A. Appendix: consumption model estimation results

1.A.1. Differenced hazard as regressor

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
diff. hazard	3.060	-0.137	5.248*	-0.156
	[1.11]	[1.02]	[1.86]	[1.14]
wave 1 hazard	-1.870	-0.461*	-1.541	-0.482*
	[0.52]	[1.89]	[0.41]	[1.91]
mother dies	0.003	0.015	-0.003	0.014
	[0.11]	[0.63]	[0.12]	[0.57]
father dies	-0.028	-0.019	-0.042	-0.028
	[0.88]	[0.63]	[1.22]	[0.87]
dln_income	0.015***	0.014***	0.017***	0.016***
	[4.08]	[4.50]	[4.15]	[4.63]
age	0.003	-0.001	0.002	-0.001
	[0.30]	[0.84]	[0.20]	[0.71]
female	0.006	-0.005	0.012	-0.008
	[0.40]	[0.64]	[0.80]	[0.91]
has child	0.021	0.023	0.015	0.016
	[0.85]	[0.99]	[0.63]	[0.73]
new_cancer	-0.352*	-0.288	-0.391*	-0.287
	[1.78]	[1.58]	[1.80]	[1.48]
new_heart attack	0.022	0.083	-0.068	0.047
	[0.22]	[1.18]	[0.64]	[0.62]
new_stroke	0.056	0.011	0.054	0.046
	[0.62]	[0.14]	[0.54]	[0.61]
new_fracture	0.044	0.075	-0.028	0.074
	[0.19]	[0.28]	[0.09]	[0.19]
new_hypertension	-0.012	0.003	-0.023	0.001
	[0.61]	[0.17]	[1.05]	[0.07]
new_high cholesterol	0.015	0.017	0.007	0.011
	[0.77]	[0.94]	[0.33]	[0.61]
new_diabetes	-0.025	-0.066*	0.003	-0.06
	[0.45]	[1.67]	[0.05]	[1.64]
new ADL limitation	-0.045	-0.05	-0.024	-0.025
	[0.76]	[1.29]	[0.38]	[0.74]
ddepression	-0.026	-0.003	-0.027	0.009
	[1.31]	[0.25]	[1.24]	[0.69]
exit_employment	-0.090***	-0.081***	-0.078**	-0.065**
	[2.84]	[2.69]	[2.44]	[2.27]
become_single	0.179***	0.195***	0.205***	0.233***
	[3.47]	[3.98]	[4.20]	[6.00]
DE	-0.067**	-0.070**	-0.064*	-0.067**
	[2.12]	[2.34]	[1.83]	[2.19]
SE	-0.041	-0.029	-0.052	-0.032
	[1.21]	[0.98]	[1.37]	[1.03]
NL	-0.073*	-0.053*	-0.068	-0.044
	[1.86]	[1.74]	[1.64]	[1.44]
ES	-0.018	0.012	-0.034	0.007
	[0.45]	[0.38]	[0.79]	[0.22]
IT	-0.073**	-0.069**	-0.074*	-0.071**
	[2.06]	[2.44]	[1.88]	[2.44]
FR	-0.018	-0.024	-0.013	-0.021
	[0.54]	[0.84]	[0.35]	[0.72]
DK	-0.092*	-0.076*	-0.052	-0.039
	[1.76]	[1.76]	[0.96]	[0.97]
GR	0.001	0.000	-0.001	-0.006
	[0.02]	[0.00]	[0.03]	[0.22]
CH	-0.130***	-0.119***	-0.120**	-0.112***
	[2.97]	[3.27]	[2.57]	[3.00]
BE	-0.043	-0.053*	-0.045	-0.054*
	[1.15]	[1.94]	[1.14]	[1.92]
Constant	-0.096	0.096	-0.070	0.099
	[0.23]	[1.40]	[0.15]	[1.45]
Observations	13,223	13,223	12,529	12,529

Absolute value of cluster robust t statistics in brackets

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

1.A.2. Increasing hazard as regressor

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
hazard incr.	0.305	-0.007	0.571	-0.001
	[0.90]	[0.58]	[1.55]	[0.05]
wave 1 hazard	-4.401	-0.298	-5.188	-0.299
	[1.13]	[1.38]	[1.33]	[1.32]
mother dies	-0.009	0.018	-0.026	0.015
	[0.28]	[0.76]	[0.76]	[0.64]
father dies	-0.046	-0.019	-0.072*	-0.028
	[1.23]	[0.65]	[1.74]	[0.89]
dln_income	0.014***	0.015***	0.015***	0.016***
	[3.91]	[4.74]	[3.88]	[4.84]
age	0.005	-0.002	0.004	-0.001
	[0.48]	[1.56]	[0.37]	[1.45]
female	-0.007	-0.009	-0.005	-0.01
	[0.57]	[1.02]	[0.41]	[1.15]
has child	0.033	0.036	0.025	0.025
	[1.24]	[1.48]	[0.98]	[1.06]
new_cancer	-0.265	-0.206	-0.306	-0.203
	[1.44]	[1.28]	[1.53]	[1.19]
new_heart attack	0.152	0.120*	0.041	0.079
	[1.19]	[1.77]	[0.37]	[1.08]
new_stroke	0.052	0.001	0.065	0.037
	[0.61]	[0.02]	[0.67]	[0.50]
new_fracture	0.036	0.079	-0.046	0.075
	[0.16]	[0.32]	[0.14]	[0.20]
new_hypertension	-0.006	0.007	-0.016	0.005
	[0.30]	[0.45]	[0.73]	[0.32]
new_high cholesterol	0.025	0.019	0.022	0.013
	[1.26]	[1.09]	[1.02]	[0.76]
new_diabetes	-0.020	-0.068*	0.005	-0.058
	[0.35]	[1.77]	[0.08]	[1.63]
new ADL limitation	-0.055	-0.070*	-0.049	-0.054
	[0.82]	[1.81]	[0.68]	[1.54]
ddepression	-0.029	-0.007	-0.029	0.004
	[1.43]	[0.54]	[1.35]	[0.34]
exit_employment	-0.107***	-0.081***	-0.109***	-0.067**
	[2.96]	[2.73]	[2.95]	[2.37]
become_single	0.214***	0.227***	0.226***	0.261***
	[4.08]	[4.89]	[4.19]	[7.04]
DE	-0.056	-0.071**	-0.035	-0.061*
	[1.59]	[2.30]	[0.92]	[1.95]
SE	-0.031	-0.024	-0.03	-0.026
	[0.90]	[0.81]	[0.78]	[0.82]
NL	-0.079*	-0.058*	-0.061	-0.046
	[1.79]	[1.83]	[1.35]	[1.47]
ES	-0.021	0.018	-0.037	0.015
	[0.46]	[0.56]	[0.78]	[0.44]
IT	-0.066*	-0.061**	-0.054	-0.062**
	[1.68]	[2.09]	[1.26]	[2.05]
FR	-0.004	-0.023	0.009	-0.019
	[0.11]	[0.77]	[0.24]	[0.62]
DK	-0.085	-0.070	-0.035	-0.032
	[1.48]	[1.61]	[0.58]	[0.80]
GR	0.019	0.005	0.036	0.001
	[0.48]	[0.21]	[0.81]	[0.04]
CH	-0.136***	-0.115***	-0.123**	-0.108***
	[2.91]	[3.14]	[2.47]	[2.86]
BE	-0.014	-0.053*	0.002	-0.052*
	[0.34]	[1.86]	[0.04]	[1.79]
Constant	-0.245	0.127*	-0.224	0.131*
	[0.47]	[1.83]	[0.42]	[1.88]
Observations	13,582	13,582	12,850	12,850

Absolute value of cluster robust t statistics in brackets

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

2. Voluntary private health insurance and health care utilization of people aged 50+

2.1. Introduction

In most of the European countries there is almost universal coverage with public health insurance, and more than 50% of health expenditures are financed by the general government. Given this institutional background does voluntary private health insurance (PHI) influence health care utilization? I focus on the utilization of hospital, general practitioner (GP), specialist and dental care among people aged 50 and over. Due to the age restriction the sample used is not representative for the whole population of the analyzed countries. However, health care utilization increases on average with age, therefore the results can be indicative for the overall health care systems. The utilization of the four types of health services is analyzed separately, since insurance coverage and other individual characteristics have different influencing effects on those. For instance, utilization of hospital care is rather determined by the health condition of the patient than by the individual utility maximizing behavior.

Despite the broad coverage with public insurance, the coverage rate with voluntary private health insurance is still not negligible in the countries analyzed. In this chapter I estimate the effects of PHI on health care utilization, and also analyze how these effects vary with some institutional characteristics of the countries. If PHI coverage increased health care utilization then that could indicate the effect of moral hazard due to the reduced prices, but could also indicate better access to health care, leading to better health conditions. Apart from dental care, in this chapter I do not find evidence that PHI coverage would increase health care utilization among people aged 50 and above in Europe. Its role is rather to provide direct access to specialists and to upgraded services.

A seminal empirical paper analyzing the effect of health insurance on the demand for medical care is of Manning et al. (1987). Based on the RAND health insurance experiment conducted in the U.S., they show that more generous health insurance plans increase the demand for outpatient services. Due to the experimental design, the authors do not have to worry about the endogeneity of health insurance coverage. Gibbons and Wilcox-Gok (1998) also find positive effect of health insurance coverage on health care utilization probability, using the National Medical Expenditure Survey from the United States. In Europe mandatory health insurance is more widespread, therefore private health insurance might have smaller role in influencing

health care utilization.

Two closely related papers which use European data are of Jones et al. (2006) and Paccagnella et al. (2008). Jones et al. (2006) find a positive effect of supplementary health insurance coverage on the probability of visiting a specialist. Their results are based on samples of four countries from the European Community Household Panel User Database (ECHP-UDB). My research differs from theirs not only in the wider country coverage of the sample used, but also in the different methodology and extended research question - I analyze the effect of PHI on hospital, GP and dental care utilization, as well. Paccagnella et al. (2008) give a detailed analysis of the determinants of voluntary PHI coverage in Europe, based on the first wave of the SHARE database.[1] They also analyze the effect of voluntary PHI on out-of-pocket expenditures, and find that this effect varies across countries. 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). They find some evidence that voluntary PHI coverage may have a positive effect on out-of-pocket medical expenditures.

This chapter contributes to the literature in providing an international comparison about the utilization enhancing effect of voluntary private health insurance coverage. An additional novelty is to analyze the effect of voluntary private health insurance coverage on the utilization of medical services if health care utilization is modelled as two-stage decision, and the endogeneity of PHI is taken into account. I identify the effect of PHI on health care utilization by using the assumption that only current employment characteristics influence the utilization, whereas past employment characteristics influence PHI coverage.

Section 2.2 provides an overview of the health care institutions and the role of private health insurance in the analyzed countries. The economic considerations underlying the empirical analysis are discussed in section 2.3. Section 2.4 presents the empirical models, and the data used is described in section 2.5. Section 2.6 discusses the empirical results, and section 2.7 concludes.

2.2. Institutional background

In the empirical analysis I investigate the effect of voluntary PHI on health care utilization in eleven European countries. Although all of these are developed countries and except for Switzerland these are EU member states, there are still considerable differences in the health care institutions. Some of these differences are related to health care financing and health care resources. The institutional background influences the role PHI has. The demand for PHI, and its effect on health care utilization depend among others on the out-of-pocket cost of medical services. If the services are covered by the mandatory public insurance then the out-of-pocket costs cannot be further reduced by the voluntary PHI. I return to further economic considerations in section 2.3.

[1] Details about the Survey of Health, Ageing and Retirement in Europe (SHARE) database are provided in section 2.5.

In this section I summarize some basic features of the health care systems in the analyzed countries. I focus on those characteristics which might indicate the role PHI has in financing health care. In Table 2.1 I present a selection of indicators related to the insurance markets and to the health care institutions. Except for the data presented in the first column, all indicators are based on aggregate statistics provided by the WHO.[2] I give a detailed explanation in section 2.5 how the PHI indicator was generated.

According to the calculated correlation coefficients, PHI coverage is more prevalent among people aged 50 or over in those countries where the public health expenditure per inhabitant or relative to GDP is higher. On the other hand, the correlation coefficient with the ratio of health expenditures covered by public sources is close to zero. Thus the demand for PHI seems to be uncorrelated with the generosity of the public health care measured by the ratio of funding coming from the government. The positive correlation of coverage rate with the last two public health expenditure indicators can be the result of the following influencing effect: more developed and widespread health care resources can increase not only the public health expenditures, but also the demand for PHI coverage.

In section 2.6.1 I present that even if a rich set of individual characteristics are controlled for, the country dummies remain significantly different from zero in the model of PHI coverage. Analyzing the influencing mechanisms of private health insurance coverage in further details is out of the scope of this chapter.

	PHI coverage ratio (%) in the sample	Public per total health expenditures (%)	Public health expenditures per inhabitant ($ ppp)	Public health expenditures per GDP (%)
AT	23.3	75.7	2,568	7.8
BE	76.1	72.9	2,172	7.0
DK	36.3	83.8	2,531	7.8
FR	84.2	79.3	2,550	8.7
DE	21.6	77.0	2,435	8.1
GR	5.2	59.1	1,189	4.3
IT	5.6	76.0	1,823	6.6
NL	81.9	64.4	1,936	5.8
ES	9.2	70.5	1,487	5.7
SE	9.1	81.8	2,425	7.6
CH	32.7	58.4	2,334	6.7
Source	SHARE	WHO	WHO	WHO

Table 2.1: Heath insurance and health expenditure indicators, 2004

In the following I summarize some further health care system characteristics of the countries included. These characteristics refer to year 2004, when the survey data I use were collected, and are based on OECD (2004), Paccagnella et al. (2008), and Thomson et al. (2009).

Except for Switzerland, all analyzed countries have mandatory public health insurance. In Switzerland there is mandatory insurance, but that is provided by private insurance companies. The coverage with the mandatory insurance is almost universal in all countries except for

[2]The WHO data are based on the WHO European health for all (HFA) database. In the WHO statistics the public health expenditure measure for Switzerland includes the expenditures covered by mandatory private health insurance.

Germany and Netherlands. In Germany the civil servants, high earners, and self employed are exempt, whereas in the Netherlands the high earners are exempt (prior to 2006).

Although there is almost universal coverage with the mandatory (public) health insurance, some cost sharing arrangements still apply in all countries. These arrangements vary across the countries. It varies to which services and to whom does the cost sharing apply, and also its magnitude differs across the countries. For example, in Austria and Sweden it applies to most services, whereas in Spain there is no cost sharing for GP or specialist care. In some countries, as in Austria, Belgium, and Italy, those with low income or with chronic health problems are exempt from the cost sharing.

Private health insurance can be the primary (principal or substitutive) health insurance for those not covered by public insurance. Otherwise, PHI can have supplementary or complementary role. Supplementary PHI covers services not insured by the public insurance. This is the most prevalent role of PHI in Europe. Complementary PHI can be contracted to cover cost sharing for services not fully financed by the public insurance. This is widespread in France, where the complementary PHI is even provided free of charge for those with low income. In the following I call "voluntary private health insurance" all those private health insurance contracts which do not have primary function. I give some additional statistics about voluntary private health insurance coverage in section 2.5.

2.3. Economic considerations

In this section I outline the economic considerations on how voluntary private health insurance coverage can affect health care utilization. My aim here is to provide some theoretical motivation to the empirical analysis. The key point is that health insurance coverage can decrease the observed costs of health services or can make higher quality of services available, both of which increase the demand for medical care.

An important assumption throughout this chapter is that PHI coverage is predetermined. The main reason for this assumption is that individuals above a given age are generally excluded from contracting PHI (details can be found in Mossialos and Thomson (2004)). The decision about buying private health insurance is likely to be made before age 50, during the earlier working life.[3] 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). 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 role e.g. in the Netherlands and in Sweden (according to Mossialos and Thomson (2004), Table 10).

[3] The question about PHI coverage is not included in the second wave of the SHARE, but there is a question about change in health insurance coverage since the last interview. Although this question is not restricted to private insurance, 89% of the respondents report no change in coverage for health problems, which indicates little time variation in insurance coverage.

Although PHI is predetermined 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 factors on the likelihood of PHI coverage.

I assume that individuals maximize a deterministic utility function, which depends on consumption and health. Future health is influenced by the 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 assumptions 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.

Expenditures on consumption goods 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. In the empirical analysis I control for the country-specific effects by including country dummies in the utilization models, and allowing country-specific effect of some observables.

Assuming positive but diminishing marginal utility of consumption and health, and positive but diminishing marginal product of medical care on health, it can be derived that the demand for health care services decreases with realized price and increases with service quality. Thus, according to a simple health care demand model, private health insurance coverage is expected to increase the demand for health services. This effect can be due to moral hazard or to the access to services unavailable without PHI coverage.[4] On the other hand, if health care prices are generally low, and utilization is determined by health problems then insurance coverage might have moderate effect on utilization. As discussed in section 2.6, the empirical results affirm the positive effect of voluntary PHI on health care utilization only partially.

2.4. Empirical models

I estimate the insurance coverage and utilization models on a pooled sample of the analyzed countries. A key modelling question is whether the partial effects of exogenous variables are the same across countries. Bago d'Uva and Jones (2009) reject the equality of income and education effects on health care utilization across European countries. However, some assumption of equality is needed in order to avoid the problem of small country-specific samples. Apart from including country dummies in the empirical models, I allow the effect of income and wealth on utilization to be country-specific. The out-of-pocket costs of health care services vary across countries, these differences imply varying effect of income and wealth on utilization. The liquidity of certain wealth components, thus their effect on health care utilization might also vary

[4] Jones et al. (2006) differentiate four influencing mechanisims of health insurance on utilization: 1. moral hazard effect due to reduced prices, 2. risk reduction effect due to reduced financial uncertainty, 3. income transfer effect (ex post transfer from the healthy to the ill), and 4. access effect due to access to high quality services.

across countries. The effect of voluntary PHI on health care utilization is also allowed to be country specific.

I consider 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 the second type of models is that many people do not utilize health care at all, and the effect of observables on the probability of utilization can be different from their effect on the positive amount of utilization.

Following the model of Grossman (1972), most empirical health care models include a rich set of regressors to capture health, and health production characteristics. This latter can include the price of health care, and standard socioeconomic variables that affect the availability of services, and capture tastes, preferences. Such empirical models of health care demand are applied among others by Hunt-McCool et al. (1994) and Gibbons and 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.

A detailed discussion about econometric issues in estimating medical care usage models is given by Jones (2000). Basic issues are that the dependent variable is not continuous, there is a large number of zero observations, which can be modelled with one-step or two-step models, and there are usually measurement problems as well.

In my empirical analysis I account for the potential endogeneity of voluntary PHI, and also for the large number of zero observations. The preferred specification is a two-part model, which takes into account both of the empirical difficulties: it models the endogenous PHI coverage and also the zero utilization decisions.

As a benchmark model, I assume that health care utilization is the result of a single decision, and treat voluntary PHI as exogenous. As a second benchmark, I relax the assumption of exogenous PHI. The preferred specification is a two-part model. In this approach I model nonzero utilization and the amount of utilization separately, and consider the voluntary PHI indicator as endogenous in both parts of the model. In this version of the model the effects of the individual characteristics are allowed to be different in the two parts of the utilization decision. For handling the endogeneity of PHI I apply bivariate probit estimation, and the method of two-stage residual inclusion (2SRI) suggested by Terza et al. (2008).

2.4.1. Benchmark model

As the benchmark case, I assume that health care utilization is a one-stage decision, and voluntary PHI coverage is exogenous in this decision. This simple model will be compared to the preferred two-part specification. 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

unrealistic. I assume negative binomial distribution, which fits the data indeed relatively well.[5]

The benchmark utilization model is the following:

$$E\left[Y_{ji}|X_i, PHI_i, \varepsilon_{1ji}\right] = \exp(X_i\beta_{1jk} + \gamma_{1jk}PHI_i + \varepsilon_{1ji}), \tag{2.1}$$

where index i refers to individual i, $j = 1, 2, 3$ differentiate the parameters and variables according to the dependent variable, and k is the country index. The dependent variable Y is either the number of doctoral visits (GP or specialist visits) or hospital nights, PHI indicates the coverage with voluntary private health insurance, and X is a vector of variables including a rich set of socioeconomic indicators that might influence health care utilization through costs, potential benefits, and preferences. In particular, X includes age, gender, marital status, dummy variable for having children, logarithmic income, logarithmic value of the main residence (replaced with zero if the reported value of the main residence is zero), education (four categories: ISCED codes 0-1, 2, 3-4 and 5-6), employment status, indicators of the current employment as civil servant, public sector employee or self employed, firm size at current employment, living area and smoking dummies (as proxies for health behavior), country dummies, and three health measures. In the outpatient care utilization models the education level and the number of health problems of the partner are also included as regressors. These can serve as proxies for the partner's health care utilization, which might induce utilization by the respondent. The effects of income, wealth, and voluntary PHI coverage are allowed to be country-specific. Further details about the data are given in section 2.5.

I assume that there is no reverse causality from health care utilization to the reported health problems within one year. This assumption is more reasonable for chronic conditions and limitations in activities of daily living than for reported symptoms, in which case it is a data limitation that health symptoms of the previous year cannot be observed.

ε_1 is a latent heterogeneity term, it is assumed that $\exp(\varepsilon_1)$ has a gamma distribution. ε_1 includes unobservables which influence health care demand, but are independent from the regressors. These can be 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.

Since spouses might make joint decisions on health care utilization (and on PHI coverage), I allow the error terms to be correlated across the household members, and the standard errors are clustered by household.

2.4.2. Second benchmark model - endogenous insurance

The assumption that PHI coverage is exogenous in the health care demand model might be unrealistic, even if it is predetermined. Time-invariant but unobserved taste shifters might be correlated both with voluntary PHI coverage and health care utilization. It can be due to adverse

[5] A simple way to check the distributional assumption is using the *nbvargr* command in Stata, written by Philip B. Ender. Nevertheless, 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.

selection and to positive selection, as well. First, the problem of adverse selection arises if those people are more likely to be covered with PHI who are more likely to utilize health care due to unobserved health problems or due to less subjective disutility attached to medical care. Second, there is positive selection if PHI is more likely to be purchased by wealthier individuals who are at the same time in better health condition, thus less likely to utilize health care. Although I control for income and wealth in the empirical models, these controls cannot capture perfectly the economic situation of the respondents. If PHI is endogenous in equation (2.1) then the consistency of the benchmark estimation is violated.

As a second benchmark, I relax the assumption of exogenous PHI, but still model the health care utilization as a one-stage decision. To handle the endogeneity of PHI I apply the method of two-stage residual inclusion (2SRI). The 2SRI method is an implementation of the method of instrumental variables 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). Provided that there are appropriate instruments for the endogenous regressor, the 2SRI method is consistent.[6] I apply maximum likelihood estimation in both stages. According to Cameron and 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 of the estimation process is a consistent estimation of the model for the endogenous regressor. The voluntary private health insurance coverage (PHI) of individual i is modelled the following way:

$$\begin{aligned} PHI_i^* &= Z_i\alpha_k + \nu_i \\ PHI_i &= 1(PHI_i^* > 0). \end{aligned} \tag{2.2}$$

The variables included in vector Z are the following: age, gender, marital status, having children, wealth and income measures, education level, living area, and country dummies, and indicators of the last employment. Again, the income and wealth variables are allowed to have country-specific effect (k is the country index). The reason for not including smoking indicators and health measures among the regressors is that PHI is considered to be predetermined, therefore I exclude those indicators that are likely to have changed since contracting the insurance.[7] The aim of this specification is to include such control variables that can capture the socioeconomic circumstances when the decision on PHI coverage was made, keeping in mind that this decision was made earlier.

The identifying instruments of voluntary PHI are indicators of the last employment: the

[6] Alternative consistent estimation methods could be to use the full-information maximum likelihood and two-stage method of moments estimation suggested by Terza (1998).

[7] Pre-existing conditions can influence coverage since those are generally excluded from voluntary PHI cover (see Mossialos and Thomson (2004)), or due to adverse selection. Analyzing the effects of long-term illness measures on PHI coverage is out of the scope of this chapter, and would also require additional data.

number of people employed at the last job ("firm size" categories), and whether the respondent was public employee, civil servant or self-employed in the last job. The firm size indicator is based on the number of employees at the current or last job. I differentiate six categories from 1 to 500 plus employees, and an additional category holds if the respondent is self-employed or the question is not applicable (25% of the respondent). Occupational status can also influence PHI coverage, as it is possible that the insurance is contracted through or supported by the employer, and in some countries different insurance regulations hold for the self-employed or civil servants. Paccagnella et al. (2008) document that in most countries covered by SHARE, voluntary PHI coverage is predominant among employees of firms with more than 24 employees. Mossialos and Thomson (2004) also report that group policies, i.e. voluntary PHI purchased by groups (typically by employers) have a major role in many European countries. Group policies generally offer lower prices and more favorable conditions, and are often provided as an employee benefit. The availability of group policies varies with firm size. The identification is based on the assumption that only the current characteristics of the employment influence health care utilization decisions, whereas the firm size at the last employment and the type of the last job influence insurance coverage. Current job characteristics might influence health care utilization e.g. through the availability of health services at the workplace or through required regular health checks. I assume that after retirement the characteristics of the last job do not have direct effect on health care utilization. Similar identification strategy is applied by Jones et al. (2006) and Paccagnella et al. (2008).

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 (2.2), 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:

$$E[Y_{ji}|X_i, PHI_i, \hat{u}_i, \varepsilon_{2ji}] = \exp(X_i\beta_{2jk} + \gamma_{2jk}PHI_i + \delta_{1j}\hat{u}_i + \varepsilon_{2ji}). \tag{2.3}$$

The notations follow that of equation (2.1). $\hat{u}$ is the first stage residual: $\hat{u}_i = PHI_i - \Phi(Z_i\hat{\alpha}_k)$, where $\Phi(.)$ 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 jth health care utilization model then δ_j should equal zero. ε_2 includes unobservables (heterogeneity components) which are independent from the included regressors.[8]

It is assumed in this model is that the coefficient of the first stage residual is not country

[8] Based on Terza et al. (2008), three conditions have to be satisfied for the consistency of the 2SRI method: 1. The identifying instruments cannot be correlated with the unobservable determinants of health care utilization. 2. The identifying instruments must be correlated with the PHI variable. 3. The identifying instruments might not have direct influence on the utilization measure, and might not be correlated with the random error term in the utilization model.

These conditions are satisfied based on the assumptions that the characteristics of the last job have no direct effect on current helath care utilization, and these characteristics are independent of the unobservable determinants of utilization.

specific. This follows from the implicit assumption that the correlation between the unobservables in the utilization and PHI coverage models is the same across the countries. Without this assumption this simple 2SRI method could not be applied for the pooled sample, and separate first stage models would be needed for all the analyzed countries.

2.4.3. Two-part model

In the preferred two-part specification I relax not only the assumption of exogenous PHI, but also that health care utilization is a one-stage decision. I allow PHI to be endogenous both in the first stage (any utilization) and second stage (amount of utilization). 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 statistical reason for applying two-stage modelling is the relatively large number of observed zero outcomes.[9]

Following the argument of Dow and Norton (2003), if zero values are "true zeros", i.e. the results of corner solution and not of sample selection then applying sample selection estimation methods can be misleading, whereas two-part models can be appropriate. In addition, Norton et al. (2008) analyze the properties of sample selection and two-part models if there is a large fraction of zero observations and there are no exclusion restrictions. They show that two-part models can be superior even if the errors in the two parts of the models are correlated. In the health care utilization models of this chapter there are no clear exclusion restrictions: the same observed characteristics drive the probability of health care utilization and the amount of utilization. This modelling feature calls for the application of two-part models, instead of selection models.

The two-part model is based on the assumption that the second stage error term has zero expected value, conditional on positive outcome and on the exogenous regressors. Based on this assumption the two parts of the model can be estimated separately.

The equations in the first part model the voluntary PHI coverage together with the probability of having any GP visits, specialist visits or hospital stays (Pos_Y_j). This first part of the model can also be estimated for dental care, for which only a binary indicator of utilization is available.

$$\begin{aligned} PHI_i^* &= Z_i\alpha_k + \nu_i \\ PHI_i &= 1(PHI_i^* > 0) \end{aligned} \tag{2.4}$$

$$\begin{aligned} Pos\_Y_{ji}^* &= X_i\beta_{3jk} + \gamma_{3jk}PHI_i + \varepsilon_{3ji} \\ Pos\_Y_{ji} &= 1(Pos\_Y_{ji}^* > 0). \end{aligned} \tag{2.5}$$

The regressors included in Z are the same as in equation (2.2), and those in X are the same as

[9] Two-stage modelling is a standard approach in modelling health care demand, see e.g. Zimmerman Murphy (1987), Pohlmeier and Ulrich (1995), and Werblow et al. (2007).

An alternative modelling strategy could be the application of finite mixture (latent class) models, as e.g. in Deb and Trivedi (1997). Such models allow for heterogeneity in the population, but do not apply strict separation between those who utilize and do not utilize health care services. Then the marginal effects are allowed to vary among "latent classes" of the population. I apply the simpler two-part modelling approach, but extend that with handling the endogeneity of PHI coverage.

in equation (2.1). Since some unobservables might affect both the voluntary PHI coverage and the decision on health care utilization, PHI can be endogenous in equation (2.5), and 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. This model handles the likely endogeneity of private health insurance in equation (2.5). The method of multivariate probit estimation in similar medical care demand framework is also applied by Gibbons and Wilcox-Gok (1998). If the exogeneity assumptions hold (Z and X are exogenous in equations (2.4) and (2.5)), the maximum likelihood estimation of the bivariate probit models gives consistent estimates.

The equations in the second part model the nonzero utilization. The nonzero numbers of doctoral visits and hospital nights are estimated by zero-truncated negative binomial regression. This regression model takes into account that the outcome values are positive counts. Again, PHI coverage can be endogenous in the utilization models, therefore I apply the method of two-stage residual inclusion: first I estimate a probit model for the probability of PHI coverage (equation (2.4)), then include the estimated residual as regressor in the zero-truncated negative binomial regression.[10]

The second part is a zero-truncated negative binomial regression. Without conditioning on positive utilization, the expected value of the outcome is:

$$E[Y_{ji}|X_i, PHI_i, \hat{u}_i, \varepsilon_{4ji}] = \exp(X_i\beta_{4jk} + \gamma_{4jk}PHI_i + \delta_{2j}\hat{u}_i + \varepsilon_{4ji}), \tag{2.6}$$

where $exp(\varepsilon_4)$ has gamma distribution. $\hat{u}$ is the first stage residual: $\hat{u}_i = PHI_i - \Phi(Z_i\hat{\alpha}_k)$, where $\Phi(.)$ is the cumulative standard normal distribution function, and $\hat{\alpha}$ indicates the estimated value of the parameter vector from the probit model.

The outcome of final interest is the expected value of utilization: $E(Y_{ji}|X_i, PHI_i) = \Pr(Y_{ji} > 0|X_i, PHI_i) \cdot E(Y_{ji}|Y_{ji} > 0, X_i, PHI_i)$, and the marginal effect of PHI coverage on overall utilization is:

$$\frac{\partial E(Y_{ji}|X_i, PHI_i)}{\partial PHI_i} = \Pr(Y_{ji} > 0|X_i, PHI_i)\frac{\partial E(Y_{ji}|Y_{ji} > 0, X_i, PHI_i)}{\partial PHI_i} + \\ + \frac{\partial \Pr(Y_{ji} > 0|X_i, PHI_i)}{\partial PHI_i}E(Y_{ji}|Y_{ji} > 0, X_i, PHI_i). \tag{2.7}$$

This marginal effect can be calculated using the estimation results of the two parts of the model.

2.5. Data

The empirical analysis is based on the first wave of the Survey of Health, Ageing, and Retirement in Europe (SHARE), release 2.3.1. The SHARE covers individuals aged 50+, and their spouses. The sample is based on probability samples in the participating countries. Since only the first

[10] The zero-truncated negative binomial models are estimated with the *ztnb* Stata command.

wave questionnaire of SHARE contains a question about private health insurance coverage, I use the first wave data, which correspond to year 2004.

I use samples on 11 European countries: Austria, Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain, Sweden, and Switzerland. In order to avoid the problem of small samples, I use pooled data for these countries, the size of the estimating sample is 23.5 thousand. I weight the observations so as each country has the same share in the pooled sample. Each weight is country specific, and equals the number of all observations divided by the number of observations in the particular country.

Due to the relatively high rate of nonresponse, for income, wealth, and health insurance premia I use the imputed values provided in the dataset. The SHARE dataset contains multiple imputations, I use the average of these. This approach is a simplification, since it neglects the uncertainty of the imputations, therefore can cause downward bias in the estimated standard errors. However, this simplification does not affect the main results of the chapter. The household-level income and wealth measures are divided by the household size so as to get individual-level measures. I generate the income measure used in this analysis as the gross income minus the health insurance payments, based on the imputed values.[11]

The key interest lies in the effect of voluntary PHI coverage on health care utilization in Europe. Coverage with voluntary PHI refers by definition only to those individuals who do not have private insurance as primary health insurance. Having primary private health insurance is relevant only in Germany and the Netherlands (the mandatory private insurance in Switzerland is defined here as public insurance). In the Netherlands the high-earners were excluded from the public insurance in 2004. In the SHARE sample 36% of the individuals living in the Netherlands report 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 (9% of the sample). I exclude those individuals from the estimation sample who are covered with primary private health insurance. The reason for this exclusion is that my aim in this chapter is to analyze the difference in utilization between those who are covered with only the mandatory health insurance, and those who have voluntary PHI coverage as well.

Some descriptive statistics of the variables are reported in Appendix 2.A.1. The financial values are purchasing power parity adjusted. The adjusted values are included in the SHARE dataset, the adjustment was based on OECD purchasing power parity data. As health indicators I use the number of chronic diseases the respondents ever had, ADL limitations, and reported symptoms.[12]

[11] Since PHI is predetermined in this model, it is reasonable to subtract its costs from the disposable income measure. I replace the net income to one for whom its calculated value is zero or negative (there are 63 such observations in the sample used). The median value of annual payments for private health insurance contracts is 356 EUR, the mean is 596 EUR among those in the sample who report supplementary or complementary PHI coverage.

[12] The chronic 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 fremoral fracture.

The ADL limitations include difficulties with dressing, walking across a room, eating, bathing, getting in or

I define voluntary private health insurance coverage as having any type of private health insurance which supplements or complements the basic health insurance. Although there are questions in the SHARE about the services the private health insurance provides, I do not use this information 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 in some insurance categories there are very few observations. The coverage ratios with the basic ten insurance categories are reported in Table 2.2. The prevalence of the different categories varies across the countries. Insurance for long term and home care are generally the least widespread. 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.

	AU	BE	DK	FR	DE	GR	IT	NL	ES	SE	CH
Medical care with direct access to specialists	2.7	6.4	9.2	70.0	3.8	1.8	1.8	0.0	6.0	1.4	17.8
Medical care with an extended choice of doctors	2.6	0.2	4.9	52.0	3.5	1.3	0.7	0.0	4.3	0.5	18.5
Dental care	1.5	5.7	18.6	75.9	5.6	0.4	0.4	47.0	3.2	0.2	6.4
Larger choice of drugs and/or full drugs expenses	1.6	2.7	13.8	72.1	0.7	0.6	0.4	34.7	0.9	0.4	14.2
Extended choice of hospitals	16.5	0.1	5.3	73.7	4.2	1.5	1.7	0.0	4.3	0.5	38.2
Long term care	0.8	0.2	0.5	64.1	0.0	0.2	0.0	0.0	0.1	0.1	9.2
Nursing care at home	0.9	0.1	0.8	54.0	0.0	0.3	0.1	0.0	2.3	0.0	8.8
Home help for ADL	0.7	2.7	0.3	25.8	0.0	0.1	0.2	0.0	0.4	0.0	8.3
Full coverage of costs for doctor visits	2.1	0.8	2.0	49.7	0.0	1.0	0.5	0.0	4.1	1.2	1.7
Full coverage of costs for hospital care	6.7	59.5	1.8	12.8	5.3	2.1	1.1	0.0	3.8	0.9	5.0

Table 2.2: Percentage of individuals covered by specific types of voluntary PHI (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. Firm size also seems to have an influencing factor, although not in all countries. Paccagnella et al. (2008) analyze in details the determinants of voluntary PHI coverage of people aged 50 and over using the SHARE data. They also point out the effect of employment status.

The dependent variables I analyze in this chapter refer to the last 12 months before the interview. These are the number of times seeing or talking to general practitioners, and to specialists, the number of nights spent in hospital, and reporting visits to dentists.[13] I analyze the demand for the GP and outpatient specialist care separately, so as to check if the influencing mechanisms are different for these two types of outpatient care. The number of dental visits

out of bed, and using the toilet.

The 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.

[13] When asking about specialist visits, a showcard is shown to the respondents indicating 13 types of specialist care.

cannot be modelled, since there is no information in the SHARE data about the number of such visits. However, I can use the information if the respondent had any dental visits or not.

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 some 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. Cutting the sample at 50 reported hospital nights, GP or specialist visits implies the exclusion of less than 1% of the observations.

In Appendix 2.A.1 I present a table of country-level averages of PHI coverage and health care utilization. There are large differences in voluntary PHI coverage rates (ranging from $5-6\%$ in Greece and Italy to 84% in France). In case of Germany and the Netherlands the differences from the statistics of Table 2.1 are due to the exclusion of the respondents with primary PHI. The cross-country variation in the ratio of people reporting specialist visits, dental visits, or hospital stays is not negligible, but that is relatively small for GP visits. The majority (85%) of the respondents report some visits to general practitioners. The average number of nonzero GP visits, specialist visits, and the average length of hospital stays also show cross-country variation, here it is the number of GP visits for which the standard deviation relative to the mean is the highest. The average length of reported hospital stays is the largest in Germany (12.4), the average number of nonzero GP visits is the highest in Italy and Spain (7.7), whereas the highest average number of specialist visits can be observed in Greece (4.6). On the other hand, all these three utilization statistics are the lowest in Sweden.

The SHARE data also provide some information on the out-of-pocket expenditures on health care. The weighted average of annual out-of-pocket expenditure on inpatient services is 280 EUR for those who report nonzero hospital nights. The average annual outpatient expenditure is 130 EUR among those who report outpatient visits to general practitioners, specialists or dentist. The survey also asks if the respondent had to forego health care due to high costs: only 4% of the respondents report such difficulty, about half of them indicate that the costs of dental care were not affordable. These statistics indicate that the out-of-pocket inpatient and outpatient health expenditures are moderate in the analyzed European countries. Moral hazard due to PHI coverage is most likely to play a role in case of dental care. For the other types of health care the role of PHI is more likely to make higher quality of services available.

2.6. Estimation results

2.6.1. Voluntary private health insurance coverage

Although the focus of the chapter is on the effect of voluntary PHI on health care utilization, estimating the influencing factors of PHI coverage is needed as the first stage equation in the structural estimation.

PHI is considered as predetermined in the health care equations, but it is still likely to be endogenous. It is assumed that the observed individual characteristics included in equation (2.4) reveal permanent differences among the individuals, thus these can be used to estimate individual specific likelihoods of being covered with PHI.

The estimated coefficients of the probit model are reported in Appendix 2.A.2**.** Income is estimated to have generally significantly positive effect on insurance coverage (the reference country is Austria). The Netherlands is an exception in this respect because there the richest individuals are typically covered with primary private health insurance, which is not included in the voluntary PHI category. Higher education is also associated with higher probability of coverage. Most of the country dummy coefficients are significantly different from zero, due to the differences in the health care and insurance institutions across the countries.

Working for a big firm can indicate the availability of group policies, and accordingly its effect is significantly positive. Although the estimated likelihood of PHI does not increase monotonically with firm size at last employment, the highest firm size (with above 500 employees) implies the highest probability of coverage, ceteris paribus. As for the type of the last job, self-employment significantly increases the probability of being covered with PHI, ceteris paribus.[14]

The indicators of the firm size and employment status significantly influence the probability of coverage with PHI. This suggests that these indicators might indeed be used for identifying the effect of PHI coverage on health care utilization. When testing the joint significance of these indicators, the p-value of the Wald-test is approximately zero.

2.6.2. Benchmark estimation results

In the benchmark model I assume that health care utilization is a one stage decision, and PHI coverage is exogenous. The estimated coefficients of the benchmark model are reported in Appendix 2.A.2, the estimated country-specific coefficients of the PHI indicator are repeated in Table 2.3.[15]

Based on the benchmark negative binomial estimation results there is no clear evidence for a positive effect of voluntary PHI coverage on health care utilization. The sign of the effect on inpatient and outpatient services varies across the countries. Using 10% significance level,

[14] Based on the estimated marginal effects at the average, the probability of having PHI is 5 percentage points higher if the firm size is above 500 employees than if the firm size is between $200 - 499$. The increasing effect of self-employment at the average is 7 percentage points.

[15] The reported significance levels are always based on clustered standard errors (with clustering on the household level).

	Number of hosp. nights	Number of GP visits	Number of spec. visits
AT	0.431**	0.084	0.136
BE	0.021	-0.072**	0.076
DK	-0.316	0.122*	0.162
FR	0.269	0.152***	0.000
DE	-0.091	-0.135**	0.135
GR	0.424	-0.329**	-0.073
IT	0.795*	-0.109	-0.057
NL	0.317	0.009	0.249**
ES	-0.504	-0.069	0.239*
SE	-0.332	0.010	0.043
CH	0.473	-0.046	0.242
Observations	23,394	23,398	23,465

*, **, *** significant at the 10, 5, 1% level, respectively

Table 2.3: PHI coefficients: benchmark model

the results indicate significant positive effect on inpatient care utilization in Austria, and Italy. The estimated effect on the number of visits to general practitioners is significantly positive in France, but significantly negative in Belgium, Germany, and Greece. The negative effect can be the result of direct access to specialist. The estimated effect on specialist care utilization is positive in most of the countries, but it is significantly different from zero only in the Netherlands, and Spain.

As expected, the indicators of health problems have positive coefficients in the health care utilization models. Some of the country dummies are also significantly different from zero, indicating the differences of health care systems and health behaviors in the countries analyzed.

2.6.3. Second benchmark estimation results

Under the second benchmark specification I still assume that health care utilization is a one stage decision, but allow PHI coverage to be endogenous in the model. I present in Table 2.4 the estimated PHI coefficients. The significance levels are based on bootstrapped standard errors, using 1000 replications.

The comparison of Tables 2.3 and 2.4 indicate that the estimated effect of PHI on hospital and GP care utilization is biased upwards if the endogeneity of the insurance coverage is neglected. The estimated coefficient of the first stage residual also indicates that in case of these two service types the unobservables which imply PHI coverage also imply higher utilization. Thus this second benchmark specification clearly reveals that assuming exogenous PHI coverage leads to biased estimates, which problem is the most severe in the model of GP care.

2.6.4. Two-part model estimation results

The preferred specification follows the model described in section 2.4.3: the utilization is modelled as two-stage decision, and voluntary PHI is considered to be endogenous in both stages.

The first part of the model is about the probability of utilization. This model can be estimated for dental care utilization, as well. In Table 2.5 I present the estimated coefficients of interest

	Number of hosp. nights	Number of GP visits	Number of spec. visits
AT	-0.275	-0.638**	0.798
BE	-0.681	-0.790***	0.735
DK	-1.014	-0.598**	0.825
FR	-0.441	-0.575*	0.666
DE	-0.803	-0.857***	0.796
GR	-0.302	-1.072***	0.605
IT	0.068	-0.847***	0.619
NL	-0.390	-0.716**	0.913
ES	-1.212	-0.800***	0.907
SE	-1.053	-0.727**	0.720
CH	-0.213	-0.763**	0.899
First stage residual	0.715	0.731**	-0.670
Observations	23,394	23,398	23,465

*, **, *** significant at the 10, 5, 1% level, respectively, based on bootstrapped standard errors

Table 2.4: PHI coefficients: second benchmark (2SRI) model

based on the bivariate probit models, but I report also the estimated effect of PHI if insurance coverage is assumed to be exogenous.

	Nonzero hosp. nights		Nonzero GP visits		Nonzero spec. visits		Nonzero dent. visits	
	Probit	Bivariate probit	Probit	Bivariate probit	Probit	Bivariate probit	Probit	Bivariate probit
AT	0.191**	0.489	0.108	-0.589	0.087	0.101	0.331***	0.520*
BE	0.120*	0.409	0.193**	-0.454	0.076	0.095	0.185***	0.374
DK	-0.045	0.245	0.120	-0.529	0.026	0.044	0.466***	0.647**
FR	0.083	0.394	0.360***	-0.340	0.121*	0.142	0.064	0.269
DE	0.175*	0.502	-0.097	-0.849*	0.151*	0.172	0.006	0.209
GR	0.303*	0.693	-0.154	-0.989*	0.033	0.057	0.150	0.385
IT	0.122	0.496	-0.105	-0.944*	-0.125	-0.102	0.121	0.349
NL	0.077	0.365	0.114	-0.535	0.050	0.069	0.474***	0.659**
ES	0.074	0.423	-0.058	-0.838	0.199*	0.220	0.329***	0.541*
SE	-0.108	0.253	-0.090	-0.872*	0.018	0.040	0.170	0.390
CH	0.169	0.457	0.020	-0.629	0.306***	0.325	0.177	0.358
corr.		-0.176		0.393		-0.011		-0.112
Obs.		23,394		23,398		23,465		23,498

*, **, *** significant at the 10, 5, 1% level, respectively

Table 2.5: PHI coefficients: probit models of nonzero utilization

If the endogeneity of PHI is neglected then its effect is underestimated in absolute value for hospital, GP and dental care utilization. For specialist care utilization the estimated effects under the simple and bivariate probit models are close to each other. Despite the differences in the point estimates of the PHI coefficients under the probit and bivariate probit specifications, the estimated correlation coefficients between the error terms of the PHI and nonzero utilization models are insignificant. Thus there is no clear evidence for the endogeneity of PHI in the first stage of utilization.[16] The results also indicate that coverage with voluntary PHI increases

[16] I also test the difference between the probit and bivariate probit PHI coefficients using the bootstrap Hausman test, following Cameron and Trivedi (2009), p. 429-430. The test indicates for all four types of health care that the estimated PHI coefficients under the two specifications do not differ significantly. This implies that the exogeneity of PHI in the first stage of utilization cannot be rejected.

the probability of utilizing hospital care, visiting specialists and dentists. On the other hand, PHI coverage decreases the probability of visiting a general practitioner. However, most of the estimated coefficients are not significantly different from zero.

The estimated coefficients of PHI in the second part of the model are presented in Table 2.6. In this specification voluntary PHI is allowed to be endogenous also in the second stage of utilization decision, where the amount of utilization is analyzed for those respondents who report nonzero hospital nights or doctoral visits. The standard errors have to be adjusted for two-stage estimation. The results presented in Table 2.6 are based on bootstrapped standard errors (with 1000 replications). The adjustment of standard errors has only small effects. As these are the main results of the chapter, I also present the t statistics and the squared correlation between the actual and predicted utilization (pseudo R-squared). In addition, I also present the result of the Wald test for the joint significance of the country specific PHI coefficients.

There is some evidence that PHI is endogenous in the second stage decision on GP care utilization. The estimated coefficient of the residual from the probit model of PHI coverage is significantly positive in the second part model of GP care. The positive coefficient indicates that the unobservables increasing the probability of PHI coverage also increase the demand for GP care. On the other hand, the residual is insignificant in the hospital and specialist care models, thus PHI coverage might be exogenous in those models.[17]

One of the advantages of the here applied two-part modelling method is that it can provide information on the different effects of PHI on the probability of utilization and on the amount of utilization. However, the size of the coefficients cannot be interpreted on themselves, therefore I analyze the estimated marginal effects in section 2.6.5. In addition, in section 2.6.6 I analyze the sensitivity of the estimation results with respect to the modelling (distributional and exogeneity) assumptions.

The presented results suggest that PHI coverage might increase the probability of hospital care utilization, but decrease the length of the stay. On the other hand, being covered with PHI implies lower probability and fewer number of visits to general practitioners. There is some evidence for increased probability of specialist care utilization due to voluntary PHI coverage, but its effect on the frequency of visits is small. The pseudo R-squared and Chi-squared statistics indicate that the explanatory power of the utilization model is the smallest for specialist care, and the country specific PHI coefficients are jointly significant for hospital and GP care, but not for specialist care.

2.6.5. Analysis of the results

Due to the nonlinear nature of the empirical models, the partial effect of PHI varies among the individuals. In Table 2.7 I present the estimated marginal effect of voluntary PHI on the number

[17] The second stage estimation results are consistent if the regressors other than PHI, and the characteristics of the previous job are exogenous. In order to test the validity of the exogeneity assumptions, it is possible to calculate the nonlinear version of the Sargan test, suggested by Cameron and Trivedi (2005), p. 277. The test confirms the exogeneity assumptions.

	Number of hosp. nights	Number of GP visits	Number of spec. visits
AT	-0.500	-1.071***	0.424
	[0.59]	[2.86]	[0.65]
BE	-0.779	-1.256***	0.393
	[0.93]	[3.41]	[0.61]
DK	-0.821	-1.024***	0.550
	[0.99]	[2.74]	[0.82]
FR	-0.537	-1.028***	0.283
	[0.63]	[2.73]	[0.43]
DE	-1.020	-1.312***	0.349
	[1.19]	[3.49]	[0.53]
GR	-0.810	-1.457***	0.246
	[0.90]	[3.59]	[0.35]
IT	-0.091	-1.257***	0.478
	[0.10]	[3.12]	[0.70]
NL	-0.623	-1.198***	0.588
	[0.74]	[3.17]	[0.90]
ES	-1.564*	-1.221***	0.471
	[1.82]	[3.14]	[0.71]
SE	-0.939	-1.104***	0.408
	[1.02]	[2.79]	[0.59]
CH	-0.547	-1.209***	0.276
	[0.65]	[3.12]	[0.42]
First stage residual	0.608	1.155***	-0.360
	[0.73]	[3.10]	[0.56]
Pseudo R-squared	0.11	0.17	0.06
Chi-squared (Wald)	25.63***	35.41***	4.65
Observations	2,941	19,922	9,118

*, **, *** significant at the 10, 5, 1% level, respectively,
based on bootstrapped standard errors; t statistics in brackets

Table 2.6: PHI coefficients: zero-truncated negative binomial models of nonzero utilization

of hospital nights and doctoral visits for a representative individual. Using the estimating sample the mode of the discrete regressors are determined. For the rest of the regressors the mean values are used, and the marginal effect of the insurance indicator is calculated for this representative individual.

The marginal effects presented in Tables 2.7 and 2.8 are based on the estimation results as discussed in sections 2.6.2-2.6.4. The results of Table 2.7 refer to overall utilization, not only to nonzero utilization.[18] The two-part model (2PM) estimates are based on the combination of the first and second part of the model, as described under equation (2.7) in section 2.4.3.

Except for Denmark and Sweden, PHI coverage has positive marginal effect on the expected number of hospital nights, based on the two-part model estimates. The positive overall effects are due to the positive effect of PHI in the first stage of utilization. However, the positive marginal effect on the probability of inpatient care utilization is insignificant for all countries. The estimated increase in the overall number of hospital nights due to PHI coverage varies between 0.1 (Spain) and 0.9 (Greece), according to the two-part model results. Thus, these

[18] The *mfx* command of Stata 10 is used when calculating the marginal effects. The significance levels of the marginal effects in the two-part models are based on bootstrapped standard errors. The Stata codes of Deb et al. (2010) are used as basis for the bootstrapping procedures. 1000 replications are used.

	Number of hosp. nights			Number of GP visits			Number of spec. visits		
		Second			Second			Second	
	Benchm.	benchm.	2PM	Benchm.	benchm.	2PM	Benchm.	benchm.	2PM
AT	0.370**	-0.169	0.548	0.373	-1.906***	-2.938***	0.166	1.458	0.382
BE	0.015	-0.363	0.225	-0.235*	-2.309***	-3.184***	0.116	1.249	0.362
DK	-0.190	-0.461	-0.072	0.519*	-1.832**	-2.849***	0.205	1.513	0.494
FR	0.210	-0.258	0.303	0.630***	-1.823**	-2.771***	-0.010	1.093	0.262
DE	-0.060	-0.389	0.390	-0.469**	-2.317***	-3.568***	0.190	1.465	0.381
GR	0.366	-0.182	0.925	-1.094***	-2.632***	-3.894***	-0.088	1.008	0.159
IT	0.841	0.049	0.813	-0.614	-2.286***	-3.737***	-0.091	1.038	0.280
NL	0.255	-0.229	0.226	0.041	-2.102***	-3.100***	0.327*	1.743	0.545
ES	-0.276*	-0.496	0.104	-0.248	-2.208***	-3.459***	0.344	1.780	0.554
SE	-0.197	-0.458	-0.083	0.032	-2.069***	-3.370***	0.051	1.275	0.316
CH	0.414	-0.135	0.455	-0.151	-2.176***	-3.188***	0.345	1.724	0.440

*, **, *** significant at the 10, 5, 1% level, respectively (2PM: based on bootstrapped standard errors)

Table 2.7: Marginal effect of voluntary PHI

effects are relatively small. The two benchmark models underestimate the effect of PHI on hospital care utilization: these models cannot wholly capture the positive effect of PHI coverage on the likelihood of hospital stays.

The estimated marginal effect of voluntary PHI on the expected number of GP visits is negative for most of the countries based on all three specifications. Neglecting the endogeneity of PHI coverage in the utilization model (benchmark model) causes upward bias in the estimated effect, which becomes positive for some of the countries. The different results of the benchmark and two-part model estimations can be explained by the self-selection into PHI coverage. Due to the influencing effect of unobserved preferences, those who are covered with PHI are also more likely to visit general practitioners. Therefore the benchmark specification underestimates the negative effect of PHI coverage on the number of GP visits. On the other hand, the 2SRI estimates also indicate significantly negative effect of PHI coverage on the visits to GPs, but this effect is smaller than the two-part estimates. According to the estimates of the two-part models the marginal effect of PHI coverage on the number of GP visits for the representative individual lies between -3.9 (Greece) and -2.8 (France). For specialist care utilization the estimated marginal effect of PHI coverage is less than one, insignificant, but positive under the two-part specification for all countries. The two-part estimates predict the largest positive effect for Spain (0.6). The estimated effect of PHI coverage on specialist care utilization is higher but still insignificant under the second benchmark specification.

Based on the results of the two-part models it is possible to separately analyze the effect of PHI coverage on the probability of utilization, and on the amount of nonzero care utilized. These estimated effects are presented in Table 2.8.

For hospital care the overall estimated effect is generally positive (as shown in Table 2.7), which comes from the increasing effect of PHI coverage on the probability of utilization. On the other hand, being covered with PHI implies shorter stays in hospitals, and this estimated effect is not negligible in magnitude, although significantly different from zero only for Spain. Two explanations are possible for these findings. First, PHI coverage might make more efficient

	Hosp. nights		GP visits		Spec. visits		Dent. visits
	Prob.	Nr.	Prob.	Nr.	Prob.	Nr.	Prob.
AT	0.115	-3.111	-0.154	-2.599***	0.026	0.848	0.181**
BE	0.090	-4.420	-0.113	-3.052***	0.022	0.818	0.130
DK	0.050	-4.386	-0.140	-2.561***	0.000	1.277	0.220***
FR	0.086	-3.380	-0.084	-2.716***	0.039	0.466	0.095
DE	0.119	-4.954	-0.252	-2.873***	0.053	0.702	0.073
GR	0.181	-4.263	-0.309	-2.989***	0.003	0.395	0.134
IT	0.118	-0.775	-0.295	-2.873***	-0.059	1.041	0.125
NL	0.080	-3.653	-0.140	-2.841***	0.013	1.342	0.223***
ES	0.097	-6.065**	-0.251	-2.756***	0.069	1.066	0.189*
SE	0.053	-4.667	-0.263	-2.607***	-0.001	0.825	0.136
CH	0.106	-3.313	-0.170	-2.807***	0.114	0.527	0.125

*, **, *** significant at the 10, 5, 1% level, respectively (amount of utilization: based on bootstrapped standard errors)

Table 2.8: Marginal effect of voluntary PHI based on the two-part model

or alternative (home care) services available. Second, it is also likely that individuals with PHI coverage utilize different kinds of inpatient services than the uncovered ones. For example, general health checks induced by PHI coverage might necessitate short stays in hospitals.

Contrary to the hospital care, PHI has negative effect both on the probability and number of visits to general practitioners, and the second-stage effects are significantly different from zero for all of the countries. The marginal effect on the probability of visiting a GP is of considerable magnitude in some of the countries. For instance, PHI coverage is estimated to decrease the estimated probability for the representative individual by around 30 percentage points in Greece and Italy. The negative effect can be the result of direct access to specialists, thus those who have PHI coverage can skip the visit to the GP. An alternative explanation can be that those covered with PHI have access to more efficient treatments and preventive care, which necessitates fewer visits to GPs, ceteris paribus. This explanation is supported by the result that the probability of visiting GP does not decrease significantly, but the frequency of the visits decreases with PHI coverage.

The estimated marginal effect on the probability of visiting a specialist is generally positive, but the maximum is 11 percentage points and insignificant for all countries. The number of nonzero specialist visits are estimated to increase due to PHI coverage in all of the countries, but these results are also insignificant. Therefore these results indicate that the demand for specialist care is not responsive to the PHI status among individuals aged 50+. This finding is different from the results of Jones et al. (2006), who estimate positive effect of PHI on specialist visits. Although they apply different methodology to a set of European countries (Ireland, Italy, Portugal, and the U.K.) than I do in this chapter, the most likely explanation for the different findings lies in the age structure of the estimating sample. The findings of Jones et al. (2006) are based on a sample of individuals aged 16 and above, which suggests that specialist care utilization can be more responsive to PHI coverage among the younger generations than among the older ones.

Finally, the marginal effect of PHI coverage on the probability of dental care utilization is

also analyzed. This effect is positive for all countries, and varies between 7 (Germany) and 22 (Denmark and the Netherlands) percentage points. The substantial positive effects for Denmark and the Netherlands are reasonable, since there the main role of voluntary PHI is financing dental care (see Table 2.2).

The estimated marginal effects can be compared to the findings of other authors. The first stage utilization results are directly comparable to the results reported by Gibbons and Wilcox-Gok (1998), due to the similar methodology. Based on a U.S. sample they estimate that supplementary PHI coverage in the U.S. increases the probability of outpatient care utilization by about $2-7$ percentage points for a representative individual, depending on the type of the insurance. Based on my estimation results the marginal effect of voluntary PHI coverage on doctoral care utilization varies across the countries and across the service types. Unanimously positive effect among the outpatient services is found only for dental care. Although my results are based on a sample of elderly individuals, these estimates still indicate that PHI has smaller effect on outpatient specialist care utilization than in the U.S., but the marginal effect on the probability of visits to dentists is relatively large. The negative partial effect of voluntary PHI coverage on GP care utilization is most likely a consequence of the European health care institutions: PHI coverage often can ensure direct access to specialists. Similarly to these results, negative effect of PHI coverage on visits to general practitioners is found by Rodríguez and Stoyanova (2004) based on Spanish data, which they also explain by direct access to specialists due to private insurance. Hullegie and Klein (2010) also estimate negative effect of private insurance on doctoral visits in Germany, which they explain by receiving better medical treatment.

How do the estimated effects relate to the country-specific characteristics of the public health care system? Table 2.9 shows the correlation coefficients between the estimated marginal effects of PHI on the amount and probability of health care utilization, and the indicators of public health care. The analyzed aggregate statistics are the ones presented in Table 2.1. The marginal effects on the amount of utilization are based on the two-part model estimates as presented in Table 2.7, and the marginal effects on the probability of utilization are the ones presented in Table 2.8. I consider the probability of utilization since that is available also for dental care.

		Aggregate indicators (source: WHO)		
		Public/total health expend.	Public health expend./inhabitant	Public health expend./GDP
2PM marginal effects	Hospital	-0.51	-0.46	-0.43
	GP	0.37	0.73	0.63
	Specialist	0.00	0.15	0.03
Marginal effects on prob.	Hospital	-0.61	-0.61	-0.56
	GP	0.17	0.60	0.51
	Specialist	-0.40	0.17	0.08
	Dentist	-0.04	-0.14	-0.30

Table 2.9: Correlation coefficients between the aggregate health expenditure indicators and the estimated marginal effects of PHI on utilization

The marginal effect of PHI on the probability of hospital stays and dental visits, and on the

overall number of hospital nights is positive for most of the countries. Based on the calculated correlations, these positive effects are larger in countries where the relative measures of public health expenditure are smaller. Thus these findings indicate that the role of PHI coverage in making inpatient and dental care available is more important in countries where general government spends relatively less on health care. The estimated effect of voluntary PHI is also generally positive on the probability and amount of specialist care utilization. There is some evidence for positive correlation with the indicators of public health expenditures, but these relationships are weak. Nevertheless, since the marginal effects on specialist care utilization are small and insignificant, these correlations are less conclusive.

Contrary to the effects on hospital and dental care, the estimated effect of voluntary PHI is negative on the probability and amount of GP care utilization for all countries. These negative effects are smaller in absolute value if the public health care is more generous. This result suggests that the role of PHI coverage in ensuring direct access to specialists or higher quality services is less important in countries with relatively larger public health care systems. In countries where public health expenditures are lower there might be greater need for avoiding the gatekeeper function of general practitioners or accessing private specialist

2.6.6. Specification checks

In the following, I modify the preferred two-part models, and check how sensitive are the results to changes in the distributional and exogeneity assumptions. In column (1) under each service type in Table 2.10 I present the estimated marginal effect of the PHI indicator based on the second part of the two-part estimation, as discussed in section 2.4.3. The marginal effect is calculated at the mode of the discrete, and mean of the continuous regressors. The results in the second, third, and fourth columns of each block also correspond to the estimated effects on nonzero utilization.[19]

The estimates under column (2) for all three service types correspond to the case when voluntary PHI is still assumed to be endogenous in the first and second part of the utilization model, but standard negative binomial model is used in the second part, instead of zero-truncated negative binomial distribution. Due to the exclusion of zero observations this model is clearly misspecified. However, in case of GP care the estimated coefficients are close to the zero-truncated negative binomial (ZTNB) estimates. For all three types of utilization, neglecting the lack of zero observations shifts the estimated coefficients towards zero. The significance of the estimates is not affected by this modification. These results provide some evidence for the robustness of the preferred two-part model estimates in the sense that modifying the distributional specification in the second part of the model does not affect qualitatively the estimation results.

The third specification is a selection model with endogenous PHI. It is analogous to the presented two-part model, but this specification also models the potential correlation between

[19] The reported significance levels under the first three specifications take into account the two-stage estimation procedure: those are based on bootstrapped ((1) and (2)) or adjusted (3) standard errors. The adjustment procedure is based on Greene (2003).

	Number of hospital nights				Number of GP visits				Number of specialist visits			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	ZTNB	Neg. binom.	Selection model, MSL	ZTNB, exog. PHI	ZTNB	Neg. binom.	Selection model, MSL	ZTNB, exog. PHI	ZTNB	Neg. binom.	Selection model, MSL	ZTNB, exog. PHI
AT	-3.111	1.080	-0.515**	0.789	-2.599***	-2.507***	-0.425**	0.282	0.848	0.066	-0.216	0.147
BE	-4.420	-1.173	-1.080*	-1.280*	-3.052***	-3.009***	-1.502***	-0.448***	0.818	0.025	-0.413*	0.083
DK	-4.386	-1.292	-1.090*	-1.513	-2.561***	-2.390***	-0.560**	0.467	1.277	0.490	-0.238	0.448
FR	-3.380	0.687	-1.078*	0.513	-2.716***	-2.498***	-1.369***	0.501**	0.466	-0.247	-0.589*	-0.152
DE	-4.954	-2.544	-1.185*	-2.573***	-2.873***	-2.896***	-0.511*	-0.605**	0.702	-0.097	-0.137	-0.013
GR	-4.263	-1.190	-1.634	-1.293	-2.989***	-3.040***	-0.171	-0.965*	0.395	-0.450	-0.246	-0.234
IT	-0.775	5.571	-0.272	5.221	-2.873***	-2.790***	-0.671*	-0.339	1.041	0.205	-0.215	0.258
NL	-3.653	0.051	-1.078*	-0.185	-2.841***	-2.782***	-1.587***	-0.196	1.342	0.440	-0.405*	0.545
ES	-6.065**	-4.610**	-1.886*	-4.673***	-2.756***	-2.744***	-0.265	-0.247	1.066	0.235	-0.117	0.250
SE	-4.667	-1.830	-1.843*	-2.092	-2.607***	-2.398***	-0.235	0.239	0.825	0.014	-0.121	0.095
CH	-3.313	0.400	-0.872*	0.286	-2.807***	-2.730***	-0.742**	-0.279	0.527	-0.228	-0.391*	-0.158

*, **, *** significant at the 10, 5, 1% level, respectively, based on bootstrapped (specifications (1) and (2)) and adjusted (specification (3)) standard errors

Table 2.10: Estimated marginal effect of PHI on nonzero utilization under various specifications

the error terms of the probit model of utilization and count data model of nonzero utilization. The problem with this specification is that there is no sample selection inherent in the health care utilization model: there are observed zero and nonzero utilizations. The first part of the model is the same as in the two-part model (equations (2.4) and (2.5)). However, equation (2.6) is modified the following way:

$$E[Y_{ji}|\tilde{X}_i, PHI_i, \tilde{\varepsilon}_{4ji}] = \exp(\tilde{X}_i\tilde{\beta}_{4jk} + \tilde{\gamma}_{4jk}PHI_i + \tilde{\varepsilon}_{4ji}) := \lambda_{ji}(\tilde{\varepsilon}_{4ji}) \text{ if } Pos\_Y_{ji} = 1. \quad (2.8)$$

I assume that ν, ε_2 and $\tilde{\varepsilon}_4$ have multivariate normal distribution with mean zero and variance $1, 1, \sigma^2$, respectively. Under this assumption it is not true any more that Y has negative binomial distribution, but the normality assumption simplifies the manipulation of the likelihood function with endogenous bivariate regressor and selectivity. I also assume that the correlation coefficients between these error terms are the same across the countries.

The $\tilde{X}$ vector of regressors is the same as X, except for the exclusion restrictions which can strengthen the identification. For inpatient care utilization the living area is considered as such variable which influences the probability of hospital stay, but not the length of the stay. Living area can indicate the availability of hospitals, 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 are assumed to influence the propensity to visit a physician, but not the frequency of visits afterwards. Based on the distributional assumptions this model can be estimated with maximum simulated likelihood (MSL).[20] Simulation is needed since there is no closed form of the likelihood function.[21]

The estimated marginal effects under this specification lie the closest to the estimates of specification (2) in case of hospital care utilization. On the other hand, qualitative differences are found for the estimated effect on the number of GP and specialist visits. The differences could be explained by the fact that the selectivity model takes into account that in the second part of the model the sample is not random. However, if the selection model is reestimated with the assumption that the selectivity is exogenous then the results still differ from the two-part estimation results. Since there are no strong and theoretically founded exclusion restrictions in

[20] The contribution of the ith observation with nonzero utilization to the likelihood is

$$\begin{aligned}\Pr(Y_{ji}, Pos\_Y_{ji} = 1, PHI_i = l|X_i, Z_i) = \\ = \int \Pr(Y_{ji}, Pos\_Y_{ji} = 1, PHI_i = l|X_i, Z_i, \tilde{\varepsilon}_{4ji}) f(\tilde{\varepsilon}_{4ji}) d\tilde{\varepsilon}_{4ji} = \\ = \int \frac{\exp(-\lambda_{ji}(\tilde{\varepsilon}_{4ji}))\lambda_{ji}(\tilde{\varepsilon}_{4ji})^{Y_{ji}}}{Y_{ji}!} \Pr(Pos\_Y_{ji} = 1, PHI_i = l|X_i, Z_i, \tilde{\varepsilon}_{4ji}) f(\tilde{\varepsilon}_{4ji}) d\tilde{\varepsilon}_{4ji}.\end{aligned}$$

$f(.)$ is the normal probability density function with mean zero and variance σ^2, and l equals 0 or 1. The second term in the integral can be expressed as a function of $\tilde{\varepsilon}_{4ji}$, using the first stage bivariate probit estimation results, and the assumption of multivariate normality. In order to simplify the estimation procedure I apply two-stage maximum likelihood estimation - I estimate the bivariate probit model of equations (2.4) and (2.5) in the first stage, and use these estimation results as known in the second stage.

[21] In the simulations I use 100 draws from the Halton sequence with prime number 7. For producing the Halton draws I use the Stata code *mdraws* written by L. Cappellari and S. P. Jenkins. Cappellari and Jenkins (2006) also discuss the advantages of Halton draws in MSL estimation.

the selectivity models, the two-part model is preferred. Nevertheless, the results still confirm the negative partial effect of PHI on the number of visits to general practitioners.

As a final specification check, I compare the estimation results of the zero-truncated negative binomial models to the case when PHI coverage is assumed to be exogenous in the second part of the model. Under this specification the residual from the probit model of PHI coverage is not included in the model of nonzero health care utilization (equation (2.6)). The estimated effects of PHI on hospital nights are considerably upward biased, compared to the specification where endogeneity is taken into account (first specification). The similar holds for the estimated effect on the number of visits to general practitioners. According to these results it is important to take into account the endogeneity of PHI in the utilization models. Due to adverse selection, those covered with PHI might suffer from more severe conditions or might have different attitudes towards medical care than the uncovered ones. Neglecting this selectivity can lead to upward biased estimated effect of PHI on health care utilization. In case of outpatient specialist care such upward bias cannot be observed, the association between PHI coverage and the amount of specialist care utilization is estimated to be weak.

It follows from this analysis that neglecting the correlation between the unobserved terms of the utilization and PHI coverage models affects the estimation results, thus handling the endogeneity of PHI coverage in the utilization models is important. The specification checks also show that the estimation results are also sensitive to the modelling assumptions, in particular the choice between two-part models and selection models influences the results. Due to identification problems under the selectivity model, the two-part model is preferred here.

2.7. Conclusions

Assuming that individuals behave in utility maximizing way, health insurance coverage can influence their health care utilization decisions, and the type of health care utilized. It depends not only on the individual characteristics, but also on the country specific institutional backgrounds to what extent voluntary private health insurance coverage influences these utilization outcomes.

In this chapter I analyze the effect of voluntary private health insurance coverage on the utilization of hospital, general practitioner, specialist and dental care. The estimated effects are compared across various modelling assumptions. The size, and in some cases also the sign of the estimated effects vary with the assumptions. In the preferred specification I model health care utilization as a two-stage decision. Due to the effects of unobservables, private health insurance coverage is likely to be endogenous in health care utilization models. In this chapter I take into consideration this endogeneity also in the two-part estimation model. The specification tests show that the exogeneity assumptions about voluntary PHI have substantial effect on the estimated coefficients.

I compare the effects of voluntary private health insurance among 11 European countries. According to the results under the preferred two-part empirical specification, private health

insurance increases hospital, outpatient specialist and dental care utilization, but has a negative effect on visits to general practitioners. The effects on the expected number of hospital nights and visits to specialists are insignificant and close to zero. Both the positive effects on hospital and dental care utilization, and the negative effects on general practitioner care utilization are larger in absolute value in countries where public health care funding indicators are smaller.

The empirical results indicate that although there is almost universal coverage with public insurance in the analyzed European countries, the role of voluntary private health insurance is not negligible among individuals aged 50 and over. There is evidence that the main roles of private insurance are making inpatient and dental services available, and avoiding the otherwise compulsory visits to general practitioners when making contacts with specialists. The results presented in the chapter can be informative for health policy decisions. Supporting private health insurance coverage might increase the utilization of some types of health services (especially of dental care), and direct the demand towards more efficient service types.

The empirical results of this chapter are based on a sample which covers individuals aged 50 and over, thus for the whole population the effect of voluntary private health insurance might be different. The country specific samples are relatively small, therefore in this chapter homogenous effects of some individual characteristics on health care utilization have to be assumed across the countries. Analyzing the differences across private health insurance contract types, the effect of insurance coverage on the type of care utilized, and on the amount of health care expenditures remains for future research.

2.A. Appendix

2.A.1. Descriptive statistics

Sample mean and standard deviation of the variables (weighted data)

	mean	sd		mean	sd
age	64.96	10.19	smoking habits		
female	0.55	0.50	never	0.53	0.50
marital status			stopped	0.27	0.44
with spouse	0.68	0.47	yes	0.20	0.40
with partner	0.04	0.20	last job		
single	0.28	0.45	civil servant	0.10	0.29
child	0.88	0.32	public employee	0.17	0.38
income (1000 EUR)	20.98	74.19	self-employed	0.17	0.37
main residence (1000 EUR)	102.51	321.00	voluntary PHI	0.32	0.47
education level			# illness	1.35	1.38
primary	0.35	0.48	# ADL problems	0.20	0.76
lower secondary	0.18	0.39	# symptoms	1.45	1.62
upper secondary	0.31	0.46	firm size not relevant	0.26	0.44
tertiary	0.16	0.37	firm size 1-5	0.13	0.34
living area			firm size 6-15	0.14	0.34
big city	0.14	0.35	firm size 16-24	0.08	0.26
suburbs big city	0.16	0.37	firm size 25-199	0.23	0.42
large town	0.19	0.39	firm size 200-499	0.07	0.25
small town	0.26	0.44	firm size 500-	0.10	0.29
rural	0.25	0.43	# gp visits	4.89	7.64
employment status			# hosp.nights	1.55	7.13
retired	0.50	0.50	# specialist visits	1.57	4.56
employed, other	0.12	0.33	visit dentist	0.54	0.50
unemployed	0.03	0.17			
disabled	0.03	0.17			
homemaker	0.15	0.35			
civil servant	0.04	0.19			
self-employed	0.07	0.26			
public employee	0.07	0.25			

Voluntary private health insurance coverage and health care utilization - sample means

	Voluntary PHI coverage	Hospital stay	Visit GP	Visit specialist	Visit dentist	# hospital nights* (if hosp.>0)	# GP visits* (if GP>0)	# specialist visits* (if spec.>0)
AT	0.23	0.19	0.85	0.37	0.51	11.57	5.51	3.58
BE	0.76	0.14	0.92	0.48	0.49	9.35	6.17	3.77
DK	0.36	0.12	0.81	0.18	0.76	8.58	4.01	3.78
FR	0.84	0.15	0.93	0.46	0.44	8.92	5.75	3.63
DE	0.14	0.16	0.92	0.54	0.75	12.35	5.54	4.29
GR	0.05	0.08	0.76	0.27	0.37	8.22	5.43	4.63
IT	0.06	0.12	0.83	0.41	0.33	9.76	7.70	4.02
NL	0.72	0.11	0.80	0.40	0.57	7.50	3.71	4.18
ES	0.09	0.11	0.88	0.42	0.26	9.13	7.72	4.40
SE	0.09	0.11	0.75	0.28	0.78	6.66	2.70	3.07
CH	0.33	0.12	0.83	0.30	0.68	8.93	4.13	3.86

* Hospital nights or doctoral visits above 50 are excluded.

2.A.2. Estimated coefficients

Voluntary private health insurance coverage

	PHI		PHI
age	-0.009***	last job	
female	0.077***	civil servant	0.028
marital status		self-employed	0.204***
with partner	0.074	public employee	-0.03
single	-0.118***	living area	
log income	0.093**	suburbs big city	-0.054
log inc: DE	0.153**	large town	-0.065
log inc: SE	0.061	small town	-0.152***
log inc: NL	-0.121*	rural	-0.230***
log inc: ES	0.046	firm size 1-5	0.183***
log inc: IT	0.106	firm size 6-15	0.164***
log inc: FR	-0.087	firm size 16-24	0.077
log inc: DK	0.098	firm size 25-199	0.170***
log inc: GR	0.010	firm size 200-499	0.146***
log inc: CH	-0.106	firm size 500-	0.268***
log inc: BE	-0.010	country: DE	-2.045***
log home	0.010	country: SE	-1.201
log home: DE	0.020**	country: NL	2.626***
log home: SE	-0.003	country: ES	-0.819
log home: NL	-0.005	country: IT	-1.513*
log home: ES	0.001	country: FR	2.674***
log home: IT	-0.014	country: DK	-0.747
log home: FR	0.004	country: GR	-0.644
log home: DK	0.011	country: CH	1.431**
log home: GR	-0.028**	country: BE	1.667***
log home: CH	-0.001	Constant	-1.554***
log home: BE	-0.002	Observations	23503
education level			
lower secondary	0.136***		
upper secondary	0.360***		
tertiary	0.485***		

*, **, *** significant at the 10, 5, 1% level, respectively

Benchmark model

	Hospital night	GP visit	Specialist visit		Hospital night	GP visit	Specialist visit
age	0.027***	0.006***	-0.012***	firm size 1-5	-0.150	-0.075	-0.105
female	-0.171**	0.049**	0.147***	6-15	-0.202	-0.065	-0.094
marital status				16-24	-0.577**	-0.065	0.018
with partner	0.286*	0.004	0.071	25-199	-0.131	-0.126**	0.055
single	0.044	0.027	-0.127***	200-499	-0.030	-0.011	0.020
child	0.185*	0.001	-0.017	500-	0.132	-0.105	0.230
log income	0.025	0.026	-0.078	smoking			
log inc: DE	-0.027	-0.055	0.075	stopped	0.310***	0.016	0.132***
log inc: SE	-0.257	0.101	-0.068	yes	0.010	-0.050**	-0.153***
log inc: NL	0.352***	0.011	0.194**	PHI: AT	0.431**	0.084	0.136
log inc: ES	0.160	0.014	0.144*	PHI: DE	-0.091	-0.135**	0.135
log inc: IT	-0.077	-0.033	0.121	PHI: SE	-0.332	0.010	0.043
log inc: FR	-0.097	-0.066**	0.067	PHI: NL	0.317	0.009	0.249**
log inc: DK	0.029	-0.076	0.133	PHI: ES	-0.504	-0.069	0.239*
log inc: GR	0.100	0.031	0.108	PHI: IT	0.795*	-0.109	-0.057
log inc: CH	0.128	-0.012	0.290***	PHI: FR	0.269	0.152***	0.000
log inc: BE	-0.02	-0.052*	0.140*	PHI: DK	-0.316	0.122*	0.162
log home	-0.019	-0.006	0.007	PHI: GR	0.424	-0.329**	-0.073
log home: DE	0.019	0.010	0.001	PHI: CH	0.473	-0.046	0.242
log home: SE	-0.022	0.010	0.005	PHI: BE	0.021	-0.072**	0.076
log home: NL	-0.010	0.000	-0.007	# chronic	0.305***	0.186***	0.235***
log home: ES	0.000	0.008	-0.001	# ADL	0.187***	0.050***	0.045*
log home: IT	0.047**	-0.006	-0.005	# symptoms	0.178***	0.101***	0.187***
log home: FR	0.006	-0.001	-0.021*	country: DE	0.009	0.526	-0.304
log home: DK	0.064**	0.005	0.013	country: SE	1.454	-1.943***	0.102
log home: GR	0.031	0.012	-0.021	country: NL	-4.731***	-0.649*	-1.891**
log home: CH	0.017	0.005	0.014	country: ES	-2.422**	-0.012	-1.201
log home: BE	0.000	0.002	-0.003	country: IT	-0.531	0.541*	-0.963
education level				country: FR	0.126	0.586**	-0.274
lower secondary	0.179*	-0.009	0.175***	country: DK	-1.806	0.263	-2.233
upper secondary	0.062	-0.067***	0.267***	country: GR	-2.566***	-0.534*	-0.985
tertiary	-0.04	-0.103***	0.330***	country: CH	-2.050	-0.146	-3.043***
employment				country: BE	-0.446	0.623**	-1.188
employed, other	-0.191	-0.103*	-0.328***	partner's education level			
unemployed	-0.105	0.015	-0.048	lower secondary		0.044	0.091
disabled	1.041***	0.464***	0.569***	upper secondary		-0.043	0.018
homemaker	-0.108	0.019	-0.085*	tertiary		-0.011	0.005
civil servant	0.048	0.046	-0.296**	partner's # chronic		-0.002	0.002
self-employed	-0.451***	-0.335***	-0.358***	partner's # ADL		-0.006	0.007
public empl.	-0.367*	0.011	-0.164	partner's # symptoms		0.016	-0.007
living area				Constant	-2.150***	0.514**	0.990
suburb city	0.047	-0.009	-0.130**	Observations	23,394	23,398	23,465
large town	0.119	-0.046	-0.261***				
small town	0.220**	-0.029	-0.280***				
rural	0.094	-0.051	-0.264***				

*, **, *** significant at the 10, 5, 1% level, respectively

3. Copayments, gatekeeping, and the utilization of outpatient public and private care at age 50 and above in Europe

3.1. Introduction

In this chapter I provide some quantitative results on the relationship between the demand for health care among people aged 50 and above in Europe, the out-of-pocket costs of the health care services and the gatekeeper role of general practitioners. As an empirical novelty, I also analyze the demand for private care in relation to the health care institutions. If the utilization of health services increases with health care financing by the general government then that might indicate over-utilization, i.e. utilization above the socially optimal level. However, decreasing out-of-pocket costs might improve the overall health level of the population through making preventive and curative health services available. The utilization of private care is also of policy interest: on the one hand it can decrease the burden on the public budget and public health care facilities, on the other hand it might violate the equal accessibility of health services.

The basic difficulty in the empirical analysis is that the prices of health services realized by the patients are not observed. Therefore indirect measures are needed to analyze the relation between out-of-pocket costs and utilization. These measures are country-specific indicators of the health care system, such as indicators of cost-sharing arrangements and public health expenditures. One possibility would be to analyze the relations to health care utilization based on aggregate data. In this chapter I use household-level data instead, which has the advantage that a wide range of individual characteristics can be controlled for which are likely to influence the demand for health services. The data used is the second wave of the Survey of Health, Ageing, and Retirement in Europe (SHARE), a sample of individuals aged 50 or over, and their spouses. I analyze the utilization of three types of outpatient health services: health care provided by general practitioners, specialists, and dentists, but the emphasis is on the utilization of general practitioner and specialist care.

The main novelty of the chapter is estimating how some selected characteristics of the public health care system are related to the utilization of private outpatient care. This analysis is possible since information on private care utilization is included in the SHARE data. This is a unique feature of the data, because internationally comparable individual level or aggregate indicators on private care utilization are otherwise not available. First I apply a correlation

analysis of the relationship between the indicators of health care institutions and health care utilization. Then I apply regression analysis. The regression estimation results are robust to the choice between the linear specifications, and the nonlinear ones (multinomial logit and probit models). The main results indicate the expected associations between the analyzed financing and organizational indicators, and public and private care utilization. More generous public financing generally implies higher demand for public care and lower demand for private care, but these estimated associations are of relatively small magnitude. There is also some evidence that cost-sharing implies higher utilization of specialist care, which can be due to the higher quality of services or to reverse causality. The estimation results indicate that if someone does not have any chronic health problem in the analyzed 50+ population then the copayments required for general practitioner (GP) services decrease the likelihood of visiting a public GP by 13 percentage points, and the gatekeeping role decreases it by 11 percentage points. There are no such negative effects for those suffering from chronic illness. The estimated probability of visiting a private specialist is 4 percentage points higher if GPs act as gatekeepers, and 3 percentage points higher if there are copayments for specialist care. These effects are driven by people in the top financial wealth and income quartiles.

The chapter is structured as follows. In section 3.2 I summarize the main results of the related empirical literature. In section 3.3 I present the basic characteristics of the health care systems in the analyzed countries. The data used in the empirical analysis are described in section 3.4. I present the results of the correlation analysis in section 3.5, and the results of the regression analyses are discussed in section 3.6. Section 3.7 concludes.

3.2. Related literature

There are few empirical results about the relationship between public health expenditures and health care demand in Europe. As for the U.S., the general finding in the related literature is that health insurance coverage or higher coinsurance 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.

One strand of the related 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 and Jonsson (2000), there is 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 and Posnett (1992) based on a sample of 20 OECD countries over years $1960-87$, 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.

More information can be gained about the influencing factors of health care utilization if individual data are used. There are various approaches in the literature for relating the characteristics of health care institutions to the individual demand for medical care. The horizontal equity in utilizing inpatient and outpatient care services in 11 developed countries is analyzed by van Doorslaer et al. (2000). Their main finding is that there are only small inequities in the health care distribution. The authors relate the cross-country differences in equity to some country-specific health care characteristics as cost-sharing and gatekeeping arrangements. However, due to the complexity of the health care systems no clear patterns could be found. Bago d'Uva and Jones (2009) use the European Community Household Panel (ECHP) to analyze the determinants of outpatient care utilization in Europe - they focus on the effects of income and education. They report cross-country differences, and find that richer and more educated individuals utilize specialist care generally to a higher extent. The authors relate these findings to some institutional characteristics: copayments required and the relative importance of the private sector can contribute to socioeconomic inequities. Maurer (2007) also investigates the equity of health care utilization based on the SHARE database. He also finds that health care systems are generally equitable in the analyzed ten European countries. On the other hand, cross-country differences in the average utilization of health services are estimated even after controlling for health care needs, but these differences are not analyzed in details.

In a recent paper Bolin et al. (2009) compare the importance of individual and institutional factors in outpatient care utilization in Europe using the SHARE data, and find greater role of individual factors. However, according to their results institutional factors like physician density, copayment and gatekeeping have a greater role in determining visits to specialists than to general practitioners. Jimenez-Martin et al. (2004) also provide an international analysis of the determinants of outpatient care utilization based on the ECHP data. Their research question and empirical method is closely related to the question and methodology of this chapter, although I analyze only bivariate indicators of utilization, but with a focus on private care. Jimenez-Martin et al. (2004) find that the organizational variables have basically the expected effects, e.g. in countries where general practitioners act as gatekeepers the visits to specialists are lower, ceteris paribus. An interesting result is that fee-for-service payment schemes increase the frequency of visits to specialists - the authors conclude that this finding can indicate demand induced by the physicians.

My research differs from these papers not only in the applied sample and empirical methods, but also in the research question. The aim here is to analyze the association between various characteristics of the health care institutions and outpatient care utilization, and also to analyze if these institutional characteristics are related the demand for private health services. The main focus is on the correlation between cost-sharing indicators, the gatekeeper role of GPs, and private care utilization.

There are less empirical results about the determinants of private care utilization than of overall health care utilization. A reason for the limited information is the lack of a clear defini-

tion for private services. As Maarse (2006) points out, private practitioners are always embedded in the public regulations. Moreover, services financed from private sources are not necessarily provided by private agents. Maarse (2006) provides some evidence on the privatization of in-patient health care provision in the last ca. 20 years in eight European countries. Among the outpatient services the dental care is generally much more privatized than general practitioner or specialist services: according to Holst et al. (2001), more than two third of Europe's dentists are single private entrepreneurs. I provide some more details about the privatization of health services in section 3.3.

There is no clear empirical evidence available about the relative productivity (efficiency) of private and public health care. Hollingsworth (2003) provides a literature review and finds weak evidence that public health services might be more efficient than private ones. Related to private health care, Propper (2000) investigates a different question which is more related to my analysis. Based on data from the U.K. she analyzes the choice between private and public health care. Her main finding is that individuals who utilize private services are generally better-off and also more likely to have utilized private care in the past than those who do not utilize private services. However, in the longitudinal dimension Propper (2000) also finds considerable movements of patients between the public and private sectors. Since my empirical analysis is based on a cross-sectional sample, I analyze only the influencing factors of private care utilization, but not how persistent this utilization is over time. I make use of the cross-country variations in institutions in this analysis.

3.3. Health care financing and resources

The basic aim of this chapter is to analyze how out-of-pocket health care costs and gatekeeping by GPs are related to the demand for public and private outpatient health services among people aged 50 or more. I analyze this relationship based on international differences in health care financing. In this section I summarize those features of the health systems in the analyzed countries which are relevant for the empirical analysis.

Table 3.1 includes a set of aggregate statistics about health care resources and expenditures, in addition to the indicators of cost-sharing and the gatekeeper role of general practitioners. The differences in the relative number of health care professionals, and in the relative public and private expenditures are not negligible.[1] The number of physicians (excluding dentists) and of GPs relative to the population are the highest in Belgium and Greece, and the lowest in Poland. In Greece the relative numbers of physicians and specialists are the highest among the analyzed countries, whereas the number of GPs is one of the lowest, which can indicate a minor role of GPs. The relative number of dentists also varies across the countries, in Greece it is about four times larger than in Poland.

[1] The WHO definition of physician is a person who has completed studies in medicine at the university level. It excludes among others physicians not practising, and dentists.
The number of specialist includes the number of physicians specialized in dermatology, gynecology, ophthalmology, otorhinolaryngology, paediatrics, radiology, and urology.

The out-of-pocket (OOP) costs of outpatient services cannot be described with a single measure. One indicator is the ratio of private household out-of-pocket expenditures within the total health expenditures. However, this indicator refers to all types of health expenditures, including the costs of hospital care and medicines. Therefore additional information would be needed to estimate the effect of OOP costs of outpatient services on utilization.

The generosity of the mandatory health insurance can also influence outpatient care utilization. More generous public health system can imply not only lower OOP payments, but also less need for voluntary health insurance. Higher public health expenditures relative to the GDP and to the population can indicate better availability and higher quality of health services, which can induce demand for medical care.

The utilization of health services can be influenced by the copayment requirements. In some of the countries the patients have to pay for outpatient visits. Two main rationales for cost-sharing arrangements are to reduce the burden on the public budget, and to avoid the problem of over-utilization.

Dental services are not financed completely by the general government in any of the analyzed European countries. However, dental services are supported to some extent by the mandatory health insurance in all countries, although this support is restrictive in some of the countries. In Switzerland the dental treatment is covered by the mandatory insurance only in case of very severe and unavoidable diseases. In Italy dental care is supported only for some special groups (such as children and disabled), and in the Netherlands only preventive dental care is financed by the basic insurance. On the other hand, copayments for outpatient services provided by GPs and specialists are required only in some of the countries. The type and magnitude of copayments also differ across the countries where such arrangements exist. I summarize below the cost-sharing policies for GP and specialist care in the analyzed countries. The summary is based on Bago d'Uva and Jones (2009) and Thomson et al. (2009). The additional sources of information are indicated by country.

Austria Prior to 2006: 3.63 EUR fee per quarter applied for outpatient services, 20% cost-sharing for the self-employed and civil servants. From 2006: 10 EUR/year service fee applies for the so-called e-card which replaces the previous quarterly fee. Exemptions: children, pensioners receiving minimum pension, specified health problems. (Hofmarcher and Rack (2006))

Belgium GPs: 25% (10%), specialists: 40% (15%) copayments. The patients have to pay up-front the full fee, and then claim reimbursement. The values in brackets apply for patients in socioeconomically vulnerable groups, among others pensioners and disabled, provided that the income is below a specified limit. (Corens (2007))

Czech Republic User fees for doctoral visits were introduced only in 2008. Before 2008 the inpatient and outpatient health services were free of charge. (Ginneken et al. (2010))

	Number of suppliers per 100 thousand inhabitants				Public expend. per GDP (%)	Public expend. (PPP$) per capita	Public expend. per total (%)	Private OOP expend. per total (%)	Cost-sharing		GP gatekeeper
	Physicians	GPs	Specialists	Dentists					GP	Specialist	
AT	444.2	150.8	54.0	53.9	7.8	2737	76.0	15.9	+	+	+
BE	402.2	170.9	57.4	82.6	7.2	2406	75.9	18.9	+	+	0
CZ	356.5	70.3	73.4	67.5	6.1	1332	86.7	11.3	0	0	0
DK	340.1	68.9	23.9	83.6	8.1	2823	84.1	14.3	0	0	+
FR	345.3	168.9	43.2	68.6	8.7	2790	78.4	6.8	+	+	0
DE	345.0	66.4	51.3	75.9	8.1	2660	76.7	13.3	+	+	0
GR	534.6	24.9	80.6	127.2	5.9	1580	62.0	36.0	0	0	0
IT	365.4	78.9	.	62.8	6.9	2054	76.6	20.0	0	+	+
NL	360.5	52.0	23.6	49.3	7.4	2731	82.3	6.2	0	0	+
PL	218.0	15.2	37.8	33.0	4.3	643	69.9	25.6	0	0	+
ES	362.9	72.6	.	52.9	6.0	1757	71.3	21.5	0	0	+
SE	357.9	60.4	43.0	83.1	7.4	2548	81.6	16.2	+	+	0
CH	388.6	52.4	.	51.9	6.4	2463	59.1	30.8	+	+	0
	WHO	WHO	Eurostat	WHO	WHO	WHO	WHO	WHO			
	2006	2006	2005	2006	2006	2006	2006	2006			
	(CH:2008)	(CZ: 2008)									

Table 3.1: Health care resources and expenditures in the analyzed countries

Denmark There are no copayments for GP care and for most of the specialist services for Group 1 citizens (including 99% of the population), but specialist care is free only after a referral from a GP. The individuals choose between coverage options "Group 1" and "Group 2". The first option is the default, whereas the second option provides free choice of physicians, without referral from GP. However, the costs of the services are covered only up to the corresponding cost of patients in Group 1. (Strandberg-Larsen et al. (2007))

France There are 30% copayments: people pay 100% up-front, but health insurance funds normally reimburse 70% of doctoral visit costs. In general there are no upper limit on the services reimbursed. Patients with specified long-term illnesses are exempt from the copayments. (Sandier et al. (2004))

Germany There is 10 EUR fee for the first contact per quarter at a physician's office, and 5-10 EUR fee apply for services in ambulatory care. Exemptions: individuals suffering from chronic health problems. (Busse and Riesberg (2004))

Greece There are no copayments for outpatient GP and specialist care. However, informal payments are prevalent, partly because of the inadequate pricing system. Due to structural problems, the utilization of private care is widespread, which requires out-of-pocket payments. (Economou (2010))

Italy There are no copayments for GP consultations, but there is some evidence for informal payments. The fee of specialist care varies by regions, the maximum amount paid by patients is 36 EUR per visits. There are some exemptions from the copayments: people with chronic diseases, with disabilities, those aged above 65 with income below a minimum are exempt. (Donatini et al. (2009))

Netherlands There are no cost-sharing arrangements for GP and outpatient specialist care. (Exter et al. (2004))

Poland There are no copayments for consultations with GPs and specialists in the public sector. There is evidence that informal payments to physicians are prevalent. However, the share of primary health care in the informal payments is very small. (Gericke and Kuszewski (2005))

Spain No cost-sharing arrangements apply for GP and outpatient specialist care in the public sector. Informal payments are practically not present in the Spanish health care. (Duran et al. (2006))

Sweden Fees apply for consultations with GPs (ca. 15 EUR) and specialists (ca. 30 EUR), with a maximum of 100 EUR (900 SEK) per year. The fees vary by counties, but the maximum amount is set centrally. (Glenngard et al. (2005))

Switzerland 10% cost-sharing applies for GP and outpatient specialist services, but there is an upper limit on the copayments. In addition, people have to pay a part of the costs in the form of a deductible. This is set annually up to around 1,100 EUR (1,500 CHF), varying by insurance companies. The individuals can choose this level of annual fee, but the insurance premium depends on the level chosen. (European Observatory on Health Care Systems (2000))

Due to the international differences in the cost-sharing policies (fixed fees, proportional fees, and the mixture of these), it is not possible in the empirical analysis to control directly for the magnitude of copayments required for outpatient services. On the other hand, it is possible to differentiate the countries according to copayments are required or not. Except for Italy, this categorization is the same for the GP and specialist care in the analyzed countries. The categorization is still not trivial for the rest of the countries, since the cost-sharing regulations might vary across the population groups. I set the cost-sharing binary indicator to one in countries where official cost-sharing applies to the majority of the population. According to this differentiation, cost-sharing applies to Austria, Belgium, France, Germany, Sweden, and Switzerland in case of GP care. The list is extended with Italy in case of specialist care, since there is cost-sharing for specialist care, but not for GP care.

Apart from the health care resources, expenditures, and copayments for outpatient services, the legal status of medical doctors also differ across the countries. As a key part of the empirical analysis I analyze the demand for outpatient services provided outside the frameworks of the public health care. This demand can be influenced by the institutional settings, mainly as to what extent are substitutive or supplementary providers and services available. No comparable statistics are available about the number of practitioners outside the public health care in the analyzed countries. Therefore only some institutional characteristics can provide insights into the differences. I briefly describe the delivery of outpatient services in the following.

Austria Outpatient health services are mainly provided by independent, self-employed physicians. There are also outpatient clinics, run by the social health insurance scheme and by private individuals. In addition, hospital outpatient departments are becoming more important, which means that there is a mixture of private and public provision of outpatient services. In 2003 about 40% of the self-employed physicians in private practice were in contract with a health insurance fund. The health insurance funds also reimburse part of the fees charged by private physicians not contracted with the fund. These fees are typically higher than those charged by contracted practitioners. The contracted physicians have gatekeeper role, as they control the patient flows by referrals. (Hofmarcher and Rack (2006))

Belgium GPs mainly work in private practice, whereas specialists can either work in private practice or at an outpatient department of a hospital (hospitals are private or public non-profit organizations). Dentists are mostly self-employed practitioners, who are financed through the compulsory health insurance system. GPs have no gatekeeper function. The patients have free choice

of physicians whom they contact, and they can directly access the specialists. (Corens (2007))

Czech Republic About 95% of the primary health services were privatized in 2002, and most of the primary-care physicians (including GPs and dentists as well) work alone. The physicians contract with health insurance funds. The vast majority of outpatient specialists have also become private in the past few years, who work mainly in independent outpatient facilities, but can also work in outpatient sections of hospitals. There is no gatekeeping function of GPs. Patients have the right of free choice, but referral from a GP to specialists is still recommended, and indeed common practice. (Rokosova et al. (2005))

Denmark GPs, specialists and dentists are private, self-employed practitioners. Some of the specialists run the private practice in part-time, and work full-time in hospitals. The physicians are in agreement with, and financed by the regions through capitation or fee-for-service payment. GPs act as gatekeepers for "Group 1" citizens, thus for around 99% of the population. There are also municipal services that provide some types of primary care, e.g. home nurses, health visitors and municipal dentists. (Strandberg-Larsen et al. (2007))

France Outpatient care is provided by self-employed doctors and dentists. The majority of them work in their own practices, only about 15% of outpatient services are provided in hospitals. Most of the physicians provide the health services within the frameworks of an agreement between the professionals and the health insurance funds. In general, patients pay for the consultations, and are reimbursed through their health insurance afterwards. GPs have no gatekeeper role, but they can voluntarily become so-called referring doctors, which is similar to gatekeeping. In 2004 around 10% of GPs accepted this gatekeeping system. (Sandier et al. (2004))

Germany Outpatient care is mainly provided by private for-profit providers, who dominantly work in their solo practices. The majority of the physicians providing outpatient services are affiliated with the statutory health insurance, the rest of them practice solely for private patients. The patients have free choice of physicians. GPs are not gatekeepers, but they have coordinating functions. The patients can contact the specialists directly. However, there are initiatives for the gatekeeping system, e.g. since 2004 the sickness funds provide bonus for complying with the gatekeeping rules. (Busse and Riesberg (2004))

Greece There have been several reforms in the national health system so as to modernize and improve the availability of health services. Outpatient services are provided by public practitioners (working in health centers or in polyclinics owned by insurance funds or by local authorities) or by private practitioners. Private practitioners might be contracted with health insurance funds. Because of the relatively low quality of public services, there is high demand for health care provided by private practitioners, especially in case of dental care. GPs have no gatekeeper or referral role in Greece, which is partly due to the low number of GPs. (Economou (2010))

Italy GPs contract with the government, and work typically in single practices, although financial incentives are provided to physicians who share clinic premises with their colleagues. The GPs are gatekeepers in accessing the secondary health services, however some specialist services (e.g. gynecology and optometric services) can be accessed directly. Specialized outpatient services are provided either by local health units or by accredited public and private facilities. Because of the low quality and long waiting times in the public sector, there is high demand for specialist care provided outside the national health system. (Donatini et al. (2009))

The Netherlands GPs are registered at the government, have private practices, and typically work individually. Similar settings hold for dentists. Outpatient specialist services are mainly provided by the outpatient facilities of the hospitals. The specialists are not employees, but are self-employed and contract with the hospitals. GPs act as gatekeepers in the Dutch health care system, and the majority of medical problems are treated by them, which indicates that the gatekeeping system is efficient in the Netherlands. (Exter et al. (2004))

Poland GPs (family doctors) are contracted with sickness funds on capitation fee, and have an increasing role in the Polish health system. With some exceptions, specialist services are available only with a referral from the GP, thus the family doctors have gatekeeper role. Outpatient specialist care is provided either by private practitioners or by independent health care institutions. Outpatient and inpatient care are strictly separated in the Polish system. Primary dental care is almost entirely provided by private dentists. (Gericke and Kuszewski (2005))

Spain There is an integrated public system of GP care. Primary care provision is basically publicly owned and staffed. GPs act as gatekeepers, and may refer patients to specialized services if necessary. However, there are some service types for which referral is not needed, including dental and ophthalmologist care. Inpatient and outpatient specialist care are integrated to a single level, although there are some regional differences in the provision. There is a mixture of private and public ownership in inpatient and outpatient specialist care provision. Some dental services are provided by the publicly funded primary care network, the rest of the dental services are in the private sector. (Duran et al. (2006))

Sweden The provision of outpatient services varies by counties. GP and specialist care are mainly publicly provided, but there are also private providers. Private health centers and practitioners are more common in cities and urban regions. Private providers typically contract with a county council and are reimbursed with public funds for seeing patients. It also varies across the counties if GPs have gatekeeping role, but in some areas there is a lack of GPs. Dental care is provided by county council dental care organizations and by private care providers. (Glenngard et al. (2005))

Switzerland Most of the outpatient health services (including dental care) are provided by independent practitioners. Some hospitals also offer outpatient health services. Patients have free choice of doctors, and have direct access to ambulatory specialist care. These factors contribute to the relatively high number of outpatient contacts in Switzerland. The ambulatory care is mainly financed by the compulsory health insurance, and by out-of-pocket payments. (European Observatory on Health Care Systems (2000))

As indicated in this overview, the countries can be differentiated on the basis if GPs have a gatekeeper role. GPs have gatekeeper role in a given country if a consultation with a GP is required for contacting a specialist. GPs are gatekeepers in the following countries: Austria, Denmark, Italy, the Netherlands, Poland, and Spain.[2]

Based on the summary provided above, it is clear that outpatient services are provided to a large extent by private practitioners in the analyzed countries. Therefore the question of interest in the empirical analysis is not the demand for private care per se, but for such services which are out of the public health care system.

3.4. Data

The empirical analysis is based on the second wave of the Survey of Health, Ageing, and Retirement in Europe (SHARE), release 2.3.1. The SHARE is a panel data set, it covers individuals aged 50 or above, and their spouses. The sample is based on probability samples in the participating countries. Although the variables used in this analysis are observed both in the first and second waves of SHARE, identification by exogenous time-variation in health care systems is not possible because there are generally only small changes in the health institutions within a two-year time period.

I analyze the utilization of health care services based on the second wave of SHARE because it has wider country coverage than the first wave. The second wave of SHARE covers 14 countries, but since the imputations are not available for Ireland, I can include 13 countries in my analysis: Austria, Belgium, the Czech Republic, Denmark, France, Germany, Greece, Italy, the Netherlands, Poland, Spain, Sweden, and Switzerland. I include all these countries in the empirical analysis, since my final aim is to relate the country-specific health system characteristics to health care utilization, which requires international variation. The health care systems of these countries are comparable: these are developed countries (all are OECD members, and except for Switzerland EU members as well), and all countries have some type of mandatory health insurance scheme. I use pooled data for these countries, the size of the sample used is 30.8 thousand.

Applying individual data makes it possible to control for a wide range of individual and household specific characteristics which can influence health care utilization. For income and

[2] This classification of countries is based on the information provided in the "Health Systems in Transition" series of the WHO, as cited above.

wealth I use the imputed values provided in the data. The SHARE contains multiple imputations, and I use the average of these. I report some descriptive statistics of the variables in Appendix 3.A.1. The income and wealth measures are generated by dividing the household level measures with the household size, and the values are purchasing power parity adjusted. As health indicators I use the number of reported chronic diseases the respondents ever had, of ADL limitations, and of reported symptoms.[3]

The outcome variables I analyze in this chapter refer to outpatient care utilization in the last 12 months before the interview. These are the reported visits to GPs, specialists, and dentists.[4] In addition, I analyze the utilization of services provided by private providers. Private care utilization is defined the following way in the generic SHARE questionnaire: receiving any of the specified types of care from private providers that the respondent paid himself or through a private insurance because he would have waited too long, or could not get them as much as needed, in the National Health System. Thus, if for example GPs are private practitioners in a country, but visits to GPs are covered by the social security system then utilization of GP care is not defined as private care utilization.

	Public care			Private care		
	GP	Specialist	Dentist	GP	Specialist	Dentist
AT	82.4%	51.2%	48.2%	1.0%	2.7%	1.8%
BE	88.6%	53.0%	49.1%	1.0%	0.6%	0.5%
CZ	84.8%	50.8%	52.9%	0.2%	0.8%	1.4%
DK	77.1%	22.2%	73.9%	2.6%	0.6%	5.3%
FR	87.5%	51.2%	44.7%	2.1%	1.4%	2.7%
DE	84.1%	55.8%	73.0%	0.3%	0.2%	0.1%
GR	64.8%	29.0%	30.4%	3.2%	7.2%	7.9%
IT	83.8%	36.8%	30.2%	0.4%	12.2%	6.1%
NL	72.3%	39.5%	61.8%	0.8%	0.6%	3.5%
PL	72.7%	23.0%	19.3%	3.7%	5.7%	4.2%
ES	81.2%	34.7%	23.1%	0.8%	2.9%	3.0%
SE	66.4%	34.6%	75.0%	1.3%	1.5%	5.9%
CH	65.8%	29.9%	38.9%	8.8%	5.6%	33.6%

Table 3.2: Outpatient care utilization by countries (SHARE data)

The percentage of respondents reporting outpatient care utilization in each country is presented in Table 3.2. The binary indicator of public care utilization equals one if the respondent reports some health care utilization, but no private care utilization. The binary indicator of private care utilization equals one if the respondent reports private care utilization. The utilization

[3] The chronic health 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 fremoral fracture, Alzheimer's disease, and benign tumor.

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

The 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, incontinence, and fatigue.

[4] When asking about specialist visits, a showcard is shown to the respondents indicating a list of specialist care types. It includes among others visits to dermatologists, neurologists or rheumatologists.

of specialist and dental care varies more than the utilization of GP services. More than 60% of the respondents report public GP visits in all of the countries. Public specialist care utilization is the lowest in Denmark and Poland, whereas public dental care utilization is the lowest in the Mediterranean countries and in Poland. In Sweden the public GP care utilization is among the lowest ones, whereas dental care utilization is the highest among the countries. This can reflect some specific health system characteristics (minor role of general practitioners) in Sweden, or can be the result of good average health status.

Private care utilization also varies across the countries. It is on average the most prevalent for dental care, and the least for GP care. The highest ratio of patients report private specialist and dental care utilization in the Mediterranean countries, Poland, and Switzerland. In these countries specialist and dental health services are available only to a limited extent within the framework of the public health system. These SHARE statistics are in line with the WHO statistics presented in Table 3.1, in the sense that all three private care utilization statistics (which refer to the 50+ population) have a correlation coefficient around 0.6 with the relative amount of private health care expenditures (which refer to the total population).

In Appendix 3.A.1 I also present the mean and standard deviation of the variables used for the subsample of those individuals who report the utilization of any type of private care. These statistics reveal that those who utilize private care are somewhat younger, better-off, and in worse health status in terms of the reported chronic conditions and symptoms.

3.5. Correlations

In the first set of empirical analysis I relate the utilization of outpatient health services to aggregate indicators of the health care systems. I separately analyze the services provided by GPs, specialists, and dentists. Following the seminal paper of Grossman (1972), I assume that health care utilization is based on the utility maximizing behavior of the individuals. This assumption makes it reasonable to include a rich set of regressors in the empirical model that can indicate individual specific health and "health production" characteristics.

I do not model the amount of health care utilization, but only whether the given type of health care is utilized or not. I apply a linear probability model of health care utilization, based on which I can estimate the country specific fixed effects. I relate these fixed effects to the characteristics of the health care systems. The linear probability model has the following form:

$$\Pr\left(Y_i = 1\right) = X_i\beta + u_i, \tag{3.1}$$

where i is the individual index, and u includes unobservable terms, and the country fixed effects, as well. Y is the observed utilization. The X vector of regressors includes the following variables apart from a constant term: variables indicating the individual budget constraint (logarithm of income, housing wealth, and financial wealth), indicators of individual preferences and health behaviors (age, gender, marital status, education level, current employment status, being self

employed ever, living area, and smoking dummies), and health indicators (number of reported chronic health problems, ADL difficulties, symptoms). I allow the error terms to be correlated within countries. The model is estimated with OLS.

In the first version of the model the dependent variable is the utilization of any type of GP, specialist or dental care. In the second version the dependent variable is the utilization of private care. The estimated coefficients of these models are presented in Appendix 3.A.2. Based on the linear probability estimations I generate the residuals: $\hat{u}_i = Y_i - X_i\hat{\beta}$. I relate the country-by-country means of the residuals to the indicators of health care financing. An equivalent procedure would be to include country dummies in the regression and relate those coefficients to the health care indicators. This analysis can reveal if people are ceteris paribus more likely to utilize outpatient care in countries where for example the public health expenditures are more generous or where the GPs have no gatekeeper role.[5]

In Appendix 3.A.3 first I present the aggregate residuals from the utilization models (country fixed effects) and their relation to the ratio of public health expenditures to the total health expenditures. Next, I relate the aggregate residuals to the ratio of public health expenditures to GDP. Both sets of figures show that higher public health expenditures relative to the total health expenditures or to the GDP are associated with higher likelihood of health care utilization, holding the individual level observables fixed. This association is negative with respect to private outpatient care utilization.

The correlation of the public financing indicators with the country specific residuals is the weakest for specialist care, whereas for GP and dental care it is of similar magnitude. The association is especially weak between the residual of the public specialist care utilization model and the indicator of public health expenditures relative to total. This finding indicates that specialist care utilization is more responsive to the individual specific characteristics and less responsive to the public financing.

The residuals from the models of any type of public care utilization are correlated stronger with the ratio of public expenditures to GDP than to total expenditures. It is an intuitive finding since not only the higher expenditures can induce utilization but also higher utilization of public care can have a reverse effect on the public health expenditures relative to GDP. On the other hand, the residuals from the models of private care utilization have a stronger negative relation to the indicator of public expenditures within the total. Again, this can be the consequence of two influencing mechanisms: more generous public health care can induce the utilization of public care rather than private care, but the utilization of private care also decreases the ratio of public to total health expenditures.

I also analyze how the aggregate residuals are related to the binary indicators of copayments

[5] The utilization model could also be estimated as a probit model. Then the residuals can be generated as the observed utilization (0 or 1), minus the predicted probability of utilization. Analyzing the country specific means of these residuals gives similar results as the linar probability approach does. I prefer the OLS estimation since there the means of the residuals are equivalent to country specific fixed effects.

A drowback of the linear probability model is that the predicted utilization probability can fall outside the 0-1 interval. However, this happens in less than 5% of the cases for all utilization types, and it is even less than 1% for public specialist and dental care, and private GP care.

and of gatekeeping. In Table 3.3 I present the means of the residuals in countries with or without copayment or gatekeeping arrangements. These statistics reveal that the ceteris paribus utilization of GP and specialist care is more likely in countries where copayments are required for these services. One explanation for this finding can be that the copayments indicate higher quality of services, which induces utilization. An alternative explanation is that copayments are required due to the relatively high demand for GP and specialist care, and can aim at the reduction of over-utilization of health care. The presented statistics also indicate that the gatekeeper role of GPs can be efficient in reducing the utilization of specialist care among the 50+ population. It is also associated with lower likelihood of private GP care utilization but higher likelihood of private specialist care utilization, holding the individual level characteristics fixed. As the average utilization of private care services in the analyzed population is very low, the differences in the private care residuals indicate a high relative difference in the ceteris paribus likelihood of private care utilization.

		GP copayments		Spec. copayments		Gatekeeping	
		Yes	No	Yes	No	Yes	No
GP	Any	0.013	-0.013			-0.004	0.002
	Private	0.006	-0.001			-0.003	0.006
Spec.	Any			0.045	-0.056	-0.043	0.035
	Private			0.005	-0.006	0.006	-0.005

Table 3.3: Mean of the aggregate residuals of outpatient care utilization models, according to copayments and the gatekeeping role of GPs

3.6. Regression analysis

3.6.1. Homogeneous effects

In the second set of empirical analysis I apply regression estimations so as to quantify the relationship between outpatient care utilization and the indicators of health care institutions. In these estimations I control for a set of institutional characteristics at the same time. I analyze not only the overall demand for outpatient care, but also differentiate the demand for public and private care. Basically two contrasting influencing mechanisms drive the demand for private health services. On the one hand, the disutility attached to health services can be lower in case of private care due to the shorter waiting times or higher quality of services. On the other hand, private care is typically more costly for the patients than public care. When modeling the choice between health care types I assume that this choice is a one-stage decision: individuals choose between public care utilization, private care utilization, and no utilization at all. A similar approach in estimating the demand for private health care is followed by Propper (2000), who in her basic specification applies a multinomial logit model.

The preferred specifications are linear probability models of public and private care utilization. Since the regressors are the same in the models of the two types of utilization, the SUR estimates of public and private care utilization (following Zellner's seemingly unrelated regres-

sion model) are equivalent to the equation-by-equation OLS estimates. The estimated correlation between the unobservables of the two types of utilization are calculated using the residuals of the OLS models. The estimated standard errors of the coefficients allow for clustering on the country level. Clustering is needed since I use country level aggregate explanatory variables (following Moulton (19990)), and also there might be some unobservables which are country specific, thus correlated within countries. Using clustered standard errors has considerable effect on the statistical significance of the country specific coefficients.

The linear probability models have the following form:

$$\begin{aligned} \Pr(Y_{i1}=1) &= X_i\gamma_1 + Z_i\delta_1 + v_{i1}, \\ \Pr(Y_{i2}=1) &= X_i\gamma_2 + Z_i\delta_2 + v_{i2}, \end{aligned} \tag{3.2}$$

where Y_1 refers to public care utilization, and Y_2 to private care utilization, and index i is the individual index. I define utilization as public if the individual reports no private care utilization, and as private if he reports any private care utilization. Thus if a respondent reports both public and private care utilization then that is categorized as private care utilization. The error terms v_{i1} and v_{i2} are allowed to be correlated within the individual observations. The X vector of regressors is the same as in equation (3.1). The Z vector includes the following country specific regressors: the number of providers in the given service types, binary indicators of copayments required for GP and specialist care, and a binary indicator of the gatekeeper role of GPs. I do not include a measure of public health expenditures in these models since that regressor would clearly be subject to reverse causality. The more public health care the people utilize, the higher are the public expenditures. As the regressors of copayments and gatekeeper role are not relevant for dental care, I estimate these models only for GP and specialist care. I report the estimated coefficients of the linear models in Appendix 3.A.4, together with the estimated correlation between the error terms. These correlation coefficients are not negligible, are around minus 0.2. Both of the estimated correlation coefficients are significant at the 1% significance level.

A weakness of the OLS specification is that it is based on linear probability models of utilization, which can predict probabilities outside the $0-1$ interval. Therefore I compare the estimation results with two other specifications, the multinomial logit and multinomial probit specifications. The main weakness of these alternative specifications is that these are based on restrictive assumptions about the error terms. The models are specified the following way:

$$\begin{aligned} Y_{ij}^* &= X_i\gamma_j + Z_i\delta_j + \eta_{ij} \\ Y_i &= \arg\max(Y_{i0}^*, Y_{i1}^*, Y_{i2}^*), \end{aligned} \tag{3.3}$$

where j is the choice indicator (none, public or private), and an alternative is chosen if the

latent utility attached to that is the highest. Assuming that the η error terms have type I extreme value distribution, the model forms a multinomial logit model. Assuming independent standard normal distribution for the error terms, the model is a restricted multinomial probit model. When estimating the models I cluster the standard errors on the country level. The main problem of the multinomial logit specification is that it implies the assumption of independence from irrelevant alternatives (IIA). However, I test this assumption with the Small-Hsiao test, which indicates that in my empirical specifications the IIA assumption is not violated. The test is conducted by the *mlogtest* command of Stata. The multinomial probit model is estimated with the *mprobit* Stata command. Assuming the independence of the error terms is restrictive, but the model fails to converge if the error terms are allowed to be correlated.[6]

The estimated multinomial logit and probit models of health care utilization models are nonlinear, therefore it is difficult to interpret the magnitude of the estimated coefficients. Due to this difficulty I present in Table 3.4 the estimated marginal effects of the selected variables of interest. These effects are calculated at the median. For the OLS model the estimated coefficients are identical to the marginal effects. I analyze the estimated magnitude of those country-specific regressors which can indicate health care financing and funding structures, the gatekeeper role of GPs, and also the number of providers per thousand inhabitants. The copayment and gatekeeper indicators are binary variables, hence the marginal effects can be interpreted as the difference in the probability of utilization with and without copayment arrangements or gatekeeper function of GPs. For the sake of comparison, in the first part of Table 3.4 I also report the estimated coefficients of interest if only one of the country specific regressors is included at a time, apart from the individual specific controls. These estimates correspond to the correlation analysis of section 3.5.

The estimated OLS coefficients of copayments, gatekeeper role, and the number of providers are qualitatively robust to the inclusion of the country specific regressors one-by-one or jointly. The only exception here is the coefficient of the indicator of GP copayments, which has reverse sign under the two specification. In addition, the estimated association between public specialist care utilization, and copayments and gatekeeper role are significantly different from zero only under the first set of estimates. The estimates based on the multinomial logit and probit models are close to each other, thus the results are robust to the distributional assumptions implied by these models. The results of these two nonlinear model are also qualitatively similar to the linear results. This suggests that the OLS estimates can be reliably used in the further analysis.

The estimation results indicate a relatively strong but statistically insignificant negative association between copayments and the probability of public GP care utilization. In countries

[6] In general, the estimability of multinomial probit models is very problematic if there are no alternative specific regressors in the model, or if there are no exclusion restrictions across the explanatory variables of the alternative choices. These issues are discussed by Keane (1992). Even though the model is formally identified without exclusion restrictions, Keane shows that there is very small variation in the objective function from its maximum over a wide range of parameter values, and he calls this as "fragile" identification.

The general multinomial probit model can be estimated with the *asmprobit* Stata command, which also requires alternative specific regressors. Although this requirement can be circumvented with interacting some explanatory variables with the observed choice, the utilization model of this chapter still fails to converge within hundreds of iterations.

OLS - one control at a time	GP		Specialist	
	public	private	public	private
GP copay	0.038	0.003		
	[0.91]	[0.36]		
spec copay			0.108*	0.011
			[1.98]	[0.56]
GP gatekeeper	-0.008	-0.004	-0.115**	0.018
	[0.21]	[0.47]	[2.34]	[0.85]
# providers per 1000	0.127***	-0.012	0.037	0.012
	[7.10]	[1.59]	[0.94]	[1.38]

OLS	GP		Specialist	
	public	private	public	private
GP copay	-0.055	0.014		
	[1.14]	[0.81]		
spec copay			0.074	0.026
			[1.52]	[1.15]
GP gatekeeper	-0.004	0.000	-0.084	0.040
	[0.14]	[0.05]	[1.59]	[1.55]
# providers per 1000	0.156***	-0.020	0.009	0.023
	[4.37]	[1.33]	[0.28]	[1.57]

LOGIT	GP		Specialist	
	public	private	public	private
GP copay	-0.060	0.012		
	[1.26]	[0.80]		
spec copay			0.092*	0.013
			[1.70]	[1.32]
GP gatekeeper	-0.012	-0.001	-0.093	0.052
	[0.51]	[0.14]	[1.52]	[1.48]
# providers per 1000	0.169***	-0.014	0.018	0.018*
	[5.16]	[1.60]	[0.49]	[1.95]

PROBIT	GP		Specialist	
	public	private	public	private
GP copay	-0.060	0.013		
	[1.26]	[0.80]		
spec copay			0.089*	0.014
			[1.71]	[1.34]
GP gatekeeper	-0.010	-0.001	-0.093	0.053
	[0.42]	[0.15]	[1.55]	[1.54]
# providers per 1000	0.170***	-0.014*	0.016	0.020**
	[5.20]	[1.66]	[0.45]	[1.98]

* significant at 10%; * significant at 5%; * significant at 1%,
based on clustered standard errors, t statistics in brackets

Table 3.4: Estimated marginal effects at the median, based on the OLS, multinomial logit, and multinomial probit models

where copayments are required the probability of public GP care utilization is around 5 percentage point lower, holding the other factors fixed. At the same time the probability of private GP care utilization is about 1 percentage point higher. As for specialist care, the estimation results indicate that both the probability of public and private specialist care utilization is considerably higher if there are copayments. The positive association with public care is stronger than with private care. This relatively strong positive relationship can be explained either by supply side effects (i.e. demand generated by the health care providers), or by the higher quality of public specialist care if there are copayments.

If GPs have gatekeeper role in a country then the utilization of public outpatient specialist

care is less likely by more than 8 percentage points, whereas that of private specialist care is more likely by 4 percentage points. The results indicate that the probability of GP care utilization is not in an economically or statistically significant relation with the gatekeeper role of GPs. The results presented in Table 3.4 also show that the higher relative number of health care providers is associated with higher probability of public care utilization. This is an intuitive result: the higher number of providers can indicate better availability of services, and at the same time can be the consequence of higher demand for health care services. These estimated associations are stronger for public GP care than for specialist care. The significant coefficient in case of GP care can capture the cross country differences in the role GPs have in the health care systems.

The implications of the presented regression analysis differ from the implications of the correlation analysis presented in section 3.5 in case of the relation between public GP care utilization and copayments, where the correlation analysis suggests positive relationship. Such differences are reasonable since in the preferred regression analysis I control for the different institutional characteristics at the same time, therefore I can estimate the ceteris paribus effect of the included indicators. In the correlation analysis I evaluate the association with the institutional characteristics one by one, thus one correlation can capture the effect of several institutional characteristics. These differences are in line with the results presented in the top part of Table 3.4, where I control for only one institutional characteristic in each regression.

The estimation results can be compared to the related findings in the literature. Jimenez-Martin et al. (2004) find based on the ECHP data that the number of physicians increases the visits to GPs but not to specialists - according to my estimates this effect is positive or zero for both service types. They also estimate that the gatekeeper role of GPs increases the utilization of GP services but decreases that of specialist services. However, my results indicate negative effect on both care types, although very weak and insignificant on GP care, but positive effect on the utilization of private specialist care. In addition, Jimenez-Martin et al. (2004) find positive effect of public health spending on specialist visits, although they do not find clear effect on GP visits. They also analyze how the payment of doctors affects health care utilization, and find that fee-for-service payments increase specialist care utilization. This is in line with my result on the positive association between specialist care utilization and copayments. Bago d'Uva and Jones (2009) also use the ECHP data for analyzing health care utilization in Europe. Similarly to Jimenez-Martin et al. (2004) they find that the gatekeeper role of GPs decreases the utilization of specialist care, but increases the visits to GPs. Based on the SHARE data I do not find such positive effect on public GP consultations. Bago d'Uva and Jones (2009) also estimate negative effect of copayments on GP care utilization.

Bolin et al. (2009) estimate models of physician utilization based on the first wave of SHARE data. They basically find the expected effects of the institutional variables: positive effect of physician density, negative effect of copayments, and also negative effect of gatekeeping on specialist care utilization. The sign of the effect of gatekeeping on GP visits, and of copayments on specialist visits estimated by Bolin et al. (2009) are different from my estimates. There are

several potential reasons for these differences: my estimates are based on a wider range of countries, I do not analyze the number of visits, the additional control variables differ, and also the gatekeeper and copayment arrangements are defined differently - I generated these indicators based on the "Health systems in transition" series of the WHO. Nevertheless, it is a similar result that specialist care utilization is more responsive to the institutional factors, especially to the copayment and gatekeeping indicators, than the visits to GPs.

According to my knowledge, there are no directly comparable empirical studies which analyze and internationally compare the utilization of private health care services. Due to the similar methodology, the findings of Propper (2000) can be compared to the results presented in this chapter. Propper analyzes the demand for private care in the U.K., and finds that better socioeconomic status (e.g. higher income, no ADL limitations) is generally associated with higher demand for private care services. Based on the linear results estimated on the pooled SHARE data no clear results can be found about the effects of individual socioeconomic characteristics on private care utilization. The estimated effects vary across the two analyzed service types, a clear result is that higher number of reported chronic health conditions and symptoms increases the demand for private health care. For specialist care my results also indicate that the probability of utilizing private care decreases with age, but increases if someone reports being self employed ever, or lives in a big city.

3.6.2. Heterogeneous effects

To get further insights about the outpatient care utilization differences along the institutional characteristics, I reestimate the linear models of utilization, allowing for heterogeneity with financial wealth, income, age, and health status. This analysis can reveal whether those in worse financial status or worse health condition are more sensitive to the health care financing and gatekeeping arrangements. I interact the indicators of copayments and gatekeeping first with a binary indicator of having high financial wealth holding, second with high income, then with reporting at least one chronic health condition, and finally with being aged above 70. The indicator of high wealth equals one if the reported amount of financial wealth holdings is above the country specific third quartile. The third quartile has huge variation across the countries, being around 1.7 thousand Euro in Poland, and 95 thousand Euro in Switzerland. The binary indicator of high income is generated analogously, where the third quartile has again the lowest value in Poland, and the highest in Switzerland. As for the indicator of chronic health conditions, around 25% of the sample reports at least one chronic illness. Around 30% of the respondents in the sample are aged above 70. The estimated coefficients of interest are reported in Table 3.5. As the OLS models consist of a set of linear equations, these coefficients are equivalent to the estimated marginal effects.

Based on these results there is some weak evidence for heterogeneity in the relation between the analyzed indicators of health care systems and the utilization of health care. As for the GP care utilization, those with higher financial wealth are more likely to utilize private GP care, and

	GP		Specialist			GP		Specialist	
	public	private	public	private		public	private	public	private
GP copay	-0.057	0.015			GP copay	-0.054	0.016		
	[1.21]	[0.83]				[1.12]	[0.85]		
spec. copay			0.066	0.022	spec. copay			0.065	0.023
			[1.35]	[1.09]				[1.37]	[1.10]
GP gatek.	-0.002	-0.002	-0.077	0.032	GP gatek.	-0.005	-0.001	-0.080	0.032
	[0.08]	[0.24]	[1.43]	[1.42]		[0.17]	[0.16]	[1.51]	[1.38]
high fin.W·	-0.000	-0.001			high inc.·	-0.003	-0.004		
·GP copay	[0.01]	[0.29]			·GP copay	[0.69]	[1.17]		
high fin.W·			0.033*	0.017*	high inc.·			0.037***	0.016**
·spec. copay			[3.04]	[2.96]	·spec. copay			[3.28]	[2.56]
high fin.W·	-0.011	0.006	-0.025	0.024*	high inc.·	0.004	0.003	-0.016	0.028***
·GP gatek.	[1.29]	[1.71]	[1.35]	[3.03]	·GP gatek.	[0.55]	[1.06]	[0.87]	[3.45]

	GP		Specialist			GP		Specialist	
	public	private	public	private		public	private	public	private
GP copay	-0.131**	0.009			GP copay	-0.053	0.013		
	[2.46]	[0.58]				[1.06]	[0.74]		
spec. copay			0.028	0.026	spec. copay			0.076	0.025
			[0.66]	[1.38]				[1.61]	[1.10]
GP gatek.	-0.112***	-0.004	-0.121**	0.031	GP gatek.	-0.004	0.000	-0.093*	0.042
	[3.61]	[0.62]	[2.51]	[1.52]		[0.15]	[0.06]	[1.78]	[1.62]
illness·	0.101***	0.008			Above 70·	-0.005	0.006		
·GP copay	[4.17]	[1.56]			·GP copay	[0.41]	[1.54]		
illness·			0.060***	-0.001	Above 70·			-0.010	0.001
·spec. copay			[3.11]	[0.19]	·spec. copay			[0.65]	[0.29]
illness·	0.144***	0.005	0.049	0.012	Above 70·	0.002	-0.003	0.031***	-0.010**
·GP gatek.	[6.44]	[1.56]	[1.50]	[1.10]	·GP gatek.	[0.22]	[1.02]	[3.48]	[2.30]

* significant at 10%; * significant at 5%; * significant at 1%,
based on clustered standard errors, t statistics in brackets

Table 3.5: Estimated coefficients in the extended OLS models of utilization

less likely to utilize public care if GPs are gatekeepers. However, these estimated associations are not significant. The results also indicate that copayments and the gatekeeping role of GPs are associated with lower likelihood of GP visits only if someone is in a good health condition. These negative effects are not present any more for those who report chronic health problems. This finding implies that copayments can reduce the over-utilization of GP care among the healthy ones.

For specialist care utilization it can be seen that the surprising positive association between public care utilization and copayments is driven by those who have relatively high financial wealth holdings, high income, and who report bad health condition in terms of the chronic health problems. The interaction term of copayments with high income is significant even at the 1% significance level. The results also indicate that the better-off individuals are also more likely to utilize private specialist care if GPs have gatekeeper role, this finding is robust to the choice between the wealth and income indicators, and is statistically significant. Thus the gatekeeper role of GPs seems to direct some of the wealthier individuals towards private specialist care, which might reduce the burden on the public health care system. On the other hand, those aged above 70 are estimated to be less likely to turn to private specialist care.

In sum, the estimation results indicate that in the analyzed population if someone does not have any chronic health condition then the copayments required for GP services decrease the likelihood of visiting a public GP by 13 percentage points, and the gatekeeping role decreases it by 11 percentage points. However, there are no such negative effects for those suffering from chronic illness. The estimated probability of visiting a private specialist is 4 percentage points higher if GPs act as gatekeepers, and 3 percentage points higher if there are copayments for specialist care. These effects are driven by people in the top financial wealth and income quartiles. Although these estimated associations are small in absolute level, but comparing to the sample average of 3% utilizing private specialist care the relative effects are large.

3.6.3. Specification checks

In the first set of specification checks I reestimate the OLS models of section 3.6.1 with the difference that I include the indicator of public health expenditures either relative to the GDP or relative to the total health expenditures. This is a more general model than the one presented in section 3.6.1, however reverse causality makes the interpretation of these estimates difficult, these cannot be considered as causal effects. I report the estimated coefficients of interest in Table 3.6.

Public health expenditures/GDP included

	GP		Specialist	
	Public	Private	Pubic	Private
GP copay	-0.060	0.018		
	[1.40]	[1.00]		
spec. copay			0.049	0.048**
			[0.76]	[2.23]
GP gatek.	-0.006	0.001	-0.089	0.043*
	[0.20]	[0.09]	[1.71]	[1.89]
public/GDP	0.010	-0.006	0.025	-0.023***
	[0.77]	[1.11]	[1.03]	[3.94]
# providers per 1000	0.147***	-0.015	0.004	0.027**
	[3.42]	[1.12]	[0.14]	[2.34]

Public health expenditures/total included

	GP		Specialist	
	Public	Private	Pubic	Private
GP copay	-0.044	0.005		
	[0.82]	[0.54]		
spec. copay			0.079*	0.023
			[1.99]	[1.01]
GP gatek.	-0.006	0.001	-0.083*	0.039
	[0.31]	[0.30]	[1.82]	[1.47]
public/total	0.002	-0.002***	0.005*	-0.002***
	[1.15]	[3.07]	[2.12]	[3.66]
# providers per 1000	0.142***	-0.008	0.031	0.013
	[3.10]	[1.02]	[1.45]	[1.24]

* significant at 10%; * significant at 5%; * significant at 1%,
based on clustered standard errors, t statistics in brackets

Table 3.6: Estimated coefficients based on the OLS models with including indicators of public health expenditures

The estimated coefficients of copayments, gatekeeper role, and the number of providers are similar to the ones where the public expenditures indicators are not included in the utilization models (as presented in Table 3.4). In addition, these estimation results are qualitatively robust to the choice between the two measures of health expenditures. As expected, the estimated association between the public health care utilization and the expenditure measures are positive, whereas between the private care utilization and the public expenditures is negative. These findings can indicate that people are more likely to utilize private care in countries where the public health care system is less generous, but the possibility of reverse causality has to be kept in mind with respect to these results. According to these estimates, the specialist care utilization is more responsive to the generosity of public health financing, although not all of the estimated coefficients are significant statistically. The estimated probability of private specialist care utilization is around 2 percentage points lower if the ratio of public health expenditures relative to GDP is one percentage point higher, ceteris paribus.

Under the second set of specification checks I assume that outpatient care utilization is a two-stage decision. First, individuals decide on visiting a physician, second, they choose between public and private providers. The drawback of this specification is that for the sake of identification, exclusion restrictions are required between the regressors of the first and second stage models. Because of this empirical difficulty, the preferred specification is the OLS regression, as discussed in section 3.6.1.

If the efficiency of the curative services provided by public and private health care providers are the same, then the choice between these two types of care might be independent of the patient's health status. Otherwise the choice between the service types depends on the same individual and country-specific variables as the utilization decision. There are no clear results about the relative productivity (efficiency) of private and public services. Hollingsworth (2003) claims based on a literature review that public health services might be more efficient than private. Hoel and Saether (2003) assume that the productivity of the two types of services does not differ, but the disutility attached to them does. I make the identifying assumption in this two-stage specification that the second stage decision does not depend on health, and specify the utilization model accordingly. Taking into account that I model the binary choices of any type of utilization and private care utilization, I estimate Heckman probit models:

$$\begin{aligned} Y_i^* &= X_i\tilde{\gamma}_1 + Z_i\tilde{\delta}_1 + \varepsilon_i \\ Y_i &= 1\left(Y_i^* > 0\right), \\ Y\_private_{i|Y_i=1}^* &= \tilde{X}_i\tilde{\gamma}_2 + Z_i\tilde{\delta}_2 + \omega_i \\ Y\_private_{i|Y_i=1} &= 1\left(Y\_private_{i|Y_i=1}^* > 0\right), \end{aligned} \tag{3.4}$$

where Y denotes the binary indicator of utilization of either public or private care, 0 corresponding to no utilization, and $Y\_private$ denotes the binary indicator of private care utilization. The first stage of the model is about any kind of utilization. The notation follows that of equation

(3.2), so here I do not include the indicators of public health expenditures in vector Z. The second stage describes the demand for private care, conditional on utilization. The $\tilde{X}$ vector of regressors is the same as in the first stage, but the health indicators are excluded. Assuming that ε_i and ω_i have bivariate normal distribution, the model under (3.4) forms a Heckman probit model.[7]

Table 3.7 shows the estimated marginal effects based on the Heckman probit models. The errors are allowed to be correlated within countries (cluster standard errors are estimated). The calculation of the marginal effects is analogous as for the multinomial logit and probit models in section 3.6.1, which are calculated at the median. The estimated marginal effects on private care utilization are presented, not conditioned on outpatient care utilization.[8] These marginal effects are of similar magnitude as the ones based on the preferred OLS models as presented in the second part of Table 3.4. The estimated effects of the number of providers are significant at 10% significance level under the Heckman specification, and the marginal effect of copayments required for specialist care becomes smaller. Nevertheless, the two-stage modelling, the distributional assumptions, and the assumption behind the exclusion restrictions do not influence qualitatively the estimation results.

	Private GP	Private specialist
GP copay	0.013	
	[0.80]	
spec. copay		0.012
		[1.13]
GP gatek.	-0.001	0.046
	[0.16]	[1.54]
# providers per 1000	-0.014*	0.019*
	[1.63]	[1.85]

* significant at 10%; * significant at 5%; * significant at 1%, based on clustered standard errors, t statistics in brackets

Table 3.7: Estimated marginal effects on private care utilization at the median, based on the Heckman probit models

3.7. Conclusions

There are considerable differences in public and private outpatient health care utilization among the European countries. The aim of this chapter is to analyze how out-of-pocket costs of outpatient health services and the gatekeeper role of general practitioners are related to health care utilization in general, and private care utilization among individuals aged 50 and above. This analysis is possible based on cross-national observations from Europe, using the institutional variations across the countries. The individual observations make it possible to filter out the influencing role of socioeconomic characteristics and health status.

[7] The model is estimated with the *heckprob* Stata command.

[8] The presented results show the effects on the joint probability of utilizing outpatient care (being selected into the second-stage sample) and utilizing private care. These marginal effects are estimated with the *mfx* command of Stata.

Due to data limitations, it is not possible to capture the magnitude of the out-of-pocket payments with a single indicator. In the empirical analysis I include binary indicators of cost-sharing arrangements, and also analyze the association between health care utilization and indicators to what extent are health care services financed by the general government. In addition, I control for some further institutional characteristics such as the number of physicians, and the gatekeeper role of general practitioners.

After providing an overview of the health care institutions, I analyze separately the utilization of general practitioner, outpatient specialist, and dental services. Under the first approach I calculate the correlations between the country specific numerical indicators of health care institutions and the country specific fixed effects from the individual level health care utilization models. Here in the first stage I apply linear probability models of utilization. I also estimate regression models of public and private care utilization, where I control for some selected indicators of the health care institutions at the same time, and assume that the utilization of the public and private service types is a one-stage decision. As a robustness check I also estimate a Heckman probit model, assuming that utilization and the choice between public and private providers are decided sequentially. The estimated marginal effects of the country-specific indicators on private care utilization are found to be robust to the choice between these two specifications, and also to multinomial logit and probit specifications. I estimate these regression models only for general practitioner and specialist care, since for dental care there are no cross country variations whether copayments are basically required, and the gatekeeper role of general practitioners is not relevant.

The findings about the overall (public and private) outpatient care utilization are comparable to the results in the literature: the number of providers and public financing are related positively to utilization. Based on the preferred regression model, the probability of visits to general practitioners is less likely among the healthy individuals if copayments are required, and the gatekeeper role of general practitioners is associated with lower probability of utilizing public specialist care. However, there are two puzzling results: the positive association between specialist care copayments and utilization, and the lack of a positive relation between the gatekeeper role and visits to general practitioners.

The main contribution of the chapter is the analysis of private care utilization in association with health care institutions. Private care is defined as services that are provided by private providers, and are not financed by the public health insurance scheme. The utilization of such private services is moderate above age 50 in the analyzed European countries, as a consequence the health care financing indicators also have moderate association with private care utilization. Still, the estimation results indicate that copayments required for public specialist services imply higher demand for private specialist care, especially among the individuals with higher financial wealth or income. In addition, there is also some evidence that if general practitioners act as gatekeepers then that is associated with higher utilization of private outpatient specialist care, again mainly among the better-off respondents.

These results indicate that if the aim is to avoid over-utilization of outpatient public health care, then decreasing the generosity of public financing might be effective in demand reduction. The empirical results also suggest that if the out-of-pocket costs of public health care are increased or if general practitioners have a gatekeeper role then individuals partly substitute the public health services with private ones. Some weak evidence is also found that if the public financing of general practitioner visits are less generous then that decreases the utilization among the healthier individuals, thus over-utilization might be mitigated.

I conclude with some cautionary notes. The findings of the chapter are based on a sample of individuals aged 50 and above, the sensitivity of health care demand to the financing structures might be different in the overall population. The empirical analysis is based on only thirteen countries, all of which are developed European countries. Therefore the estimates related to the analyzed country-specific variables might not be valid for countries with much different health care systems. Moreover, only a limited number of institutional characteristics can be controlled for because of the limited number of countries in the sample. Reverse causality is also an important concern, as the institutional settings might be altered based on the demand for health care services. Thus endogeneity concerns remain in the regression analysis and I cannot claim causality. Finally, the identification is based on cross-country variation and not on the analysis of health care reforms, hence the policy implications of the results have to be treated carefully.

3.A. Appendix

3.A.1. Descriptive statistics

	Whole sample		Private care utilized	
	mean	std.dev.	mean	std.dev.
age	64.78	10.02	63.87	9.66
gender	1.55	0.50	1.59	0.49
marital status: with spouse	0.71	0.46	0.71	0.45
marital status: with partner	0.04	0.19	0.04	0.19
marital status: single	0.26	0.44	0.25	0.43
income (1000 EUR)	19.31	116.82	21.44	126.73
main residence (1000 EUR)	90.28	207.67	102.02	204.02
financial wealth (1000 EUR)	30.15	87.88	38.97	106.27
education: primary	0.32	0.46	0.31	0.46
education: lower secondary	0.18	0.38	0.14	0.34
education: upper secondary	0.32	0.47	0.38	0.48
education: tertiary	0.18	0.38	0.18	0.38
area: big city	0.15	0.36	0.17	0.38
area: suburbs big city	0.15	0.35	0.14	0.35
area: large town	0.19	0.39	0.20	0.40
area: small town	0.22	0.42	0.19	0.40
area: rural	0.29	0.45	0.30	0.46
employment: retired	0.53	0.50	0.50	0.50
employment: employed	0.27	0.45	0.30	0.46
employment: unemployed	0.03	0.16	0.02	0.14
employment: disabled	0.04	0.19	0.05	0.21
employment: homemaker	0.13	0.33	0.13	0.34
self employed ever	0.10	0.30	0.15	0.35
smoking: never	0.23	0.42	0.25	0.43
smoking: stopped	0.58	0.49	0.57	0.50
smoking: yes	0.20	0.40	0.19	0.39
# illness	1.64	1.52	1.89	1.70
# ADL problems	0.23	0.84	0.24	0.82
# symptoms	1.80	1.91	2.14	2.11
GP visit (binary)	0.80	0.40	0.81	0.39
specialist visit (binary)	0.43	0.49	0.61	0.49
dentist visit (binary)	0.53	0.50	0.74	0.44
Observations		30,818		2,531

3.A.2. Linear probability models of health care utilization

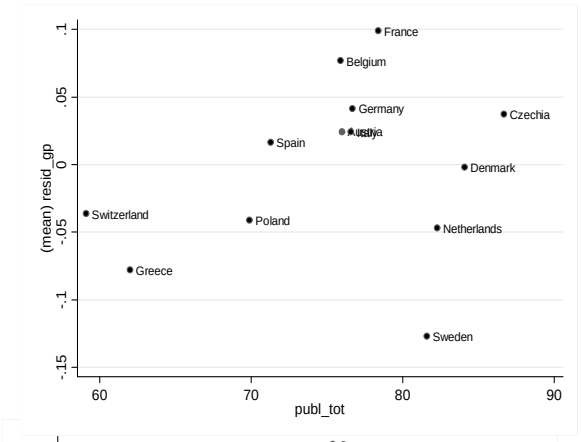
	GP		Specialist		Dentist	
	Any	Private	Any	Private	Any	Private
age	0.001	0.000	-0.004***	-0.001*	-0.006***	-0.001*
female	0.016*	0.001	0.038**	0.008**	0.069***	0.010**
mstat: with partner	-0.008	0.004	-0.033	-0.002	0.001	-0.007
mstat: single	0.002	0.002	-0.032**	-0.007	-0.045***	0.003
log income	0.006	-0.001	0.012*	-0.001	0.022***	0.002
log residence	0.001	0.000	0.000	0.001	0.000	0.000
log fin.wealth	0.003	0.000	0.007**	0.000	0.024***	0.003
edu: lower secondary	0.021	-0.005	0.078***	-0.013**	0.103***	-0.003
edu: upper secondary	0.010	0.003	0.058**	-0.004	0.167***	0.021
edu: tertiary	-0.003	0.005	0.087**	-0.006	0.236***	0.006
emp: employed	-0.055***	0.001	-0.089***	-0.004	0.012	0.008
emp: unemp.	-0.013	-0.003	-0.071**	-0.021**	-0.020	-0.011
emp: disabled	0.002	0.003	0.057*	0.003	-0.024	-0.007
emp: homemaker	-0.030*	-0.006	-0.026	0.003	-0.085**	0.003
self emp. ever	-0.056***	0.003	-0.015	0.024***	-0.014	0.019*
area: suburbs	0.010	-0.001	-0.004	-0.016**	0.035*	-0.002
area: large town	-0.004	-0.001	-0.063***	-0.013**	0.009	0.000
area: small town	0.029*	-0.004	-0.020	-0.015*	-0.011	-0.007
area: rural	0.015	-0.001	-0.050***	-0.009	-0.042	-0.005
smoke: stopped	-0.004	-0.003	0.048*	0.002	0.014	-0.002
smoke: yes	-0.065***	-0.003	-0.039	-0.003	-0.060**	-0.003
# illness	0.046***	0.001**	0.060***	0.009*	0.006	0.001
# ADL	-0.017***	0.001	-0.015**	0.000	-0.038***	-0.005**
# symptoms	0.016***	0.002**	0.033***	0.003**	0.003	0.003***
Constant	0.570***	0.011	0.303**	0.061**	0.321**	0.028
R^2	0.08	0.00	0.09	0.02	0.16	0.01

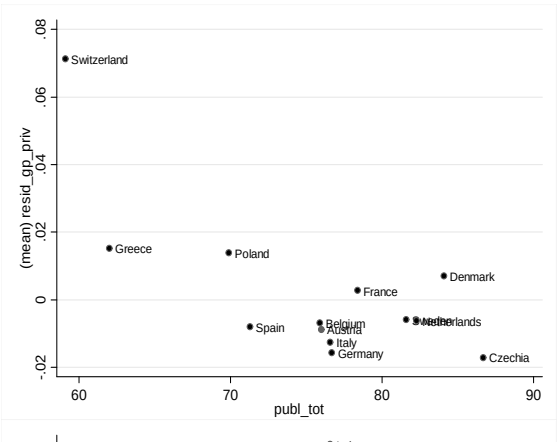
Observations: 30,818

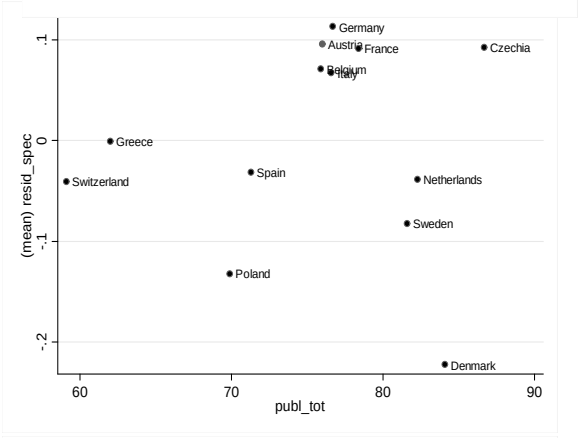
* significant at 10%; * significant at 5%; * significant at 1%, based on clustered standard errors

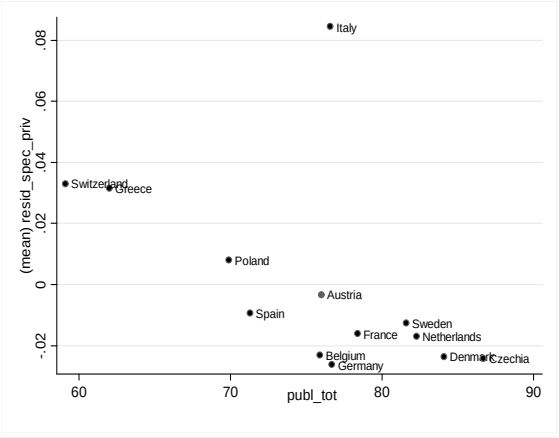
3.A.3. Correlation analysis

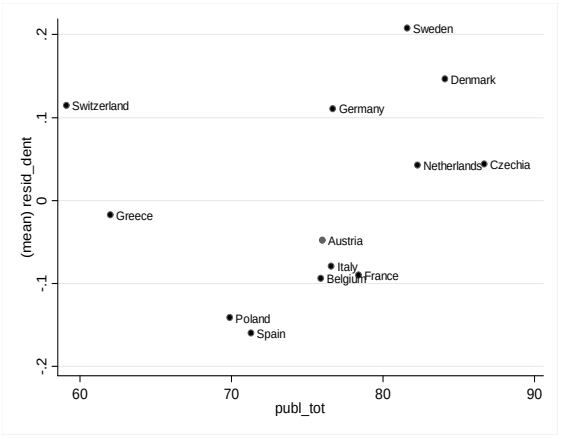
Public health expenditure relative to total and the unexplained part of outpatient care utilization (aggregate residuals)

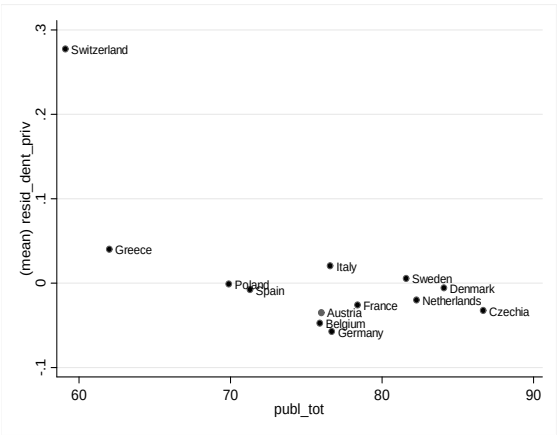




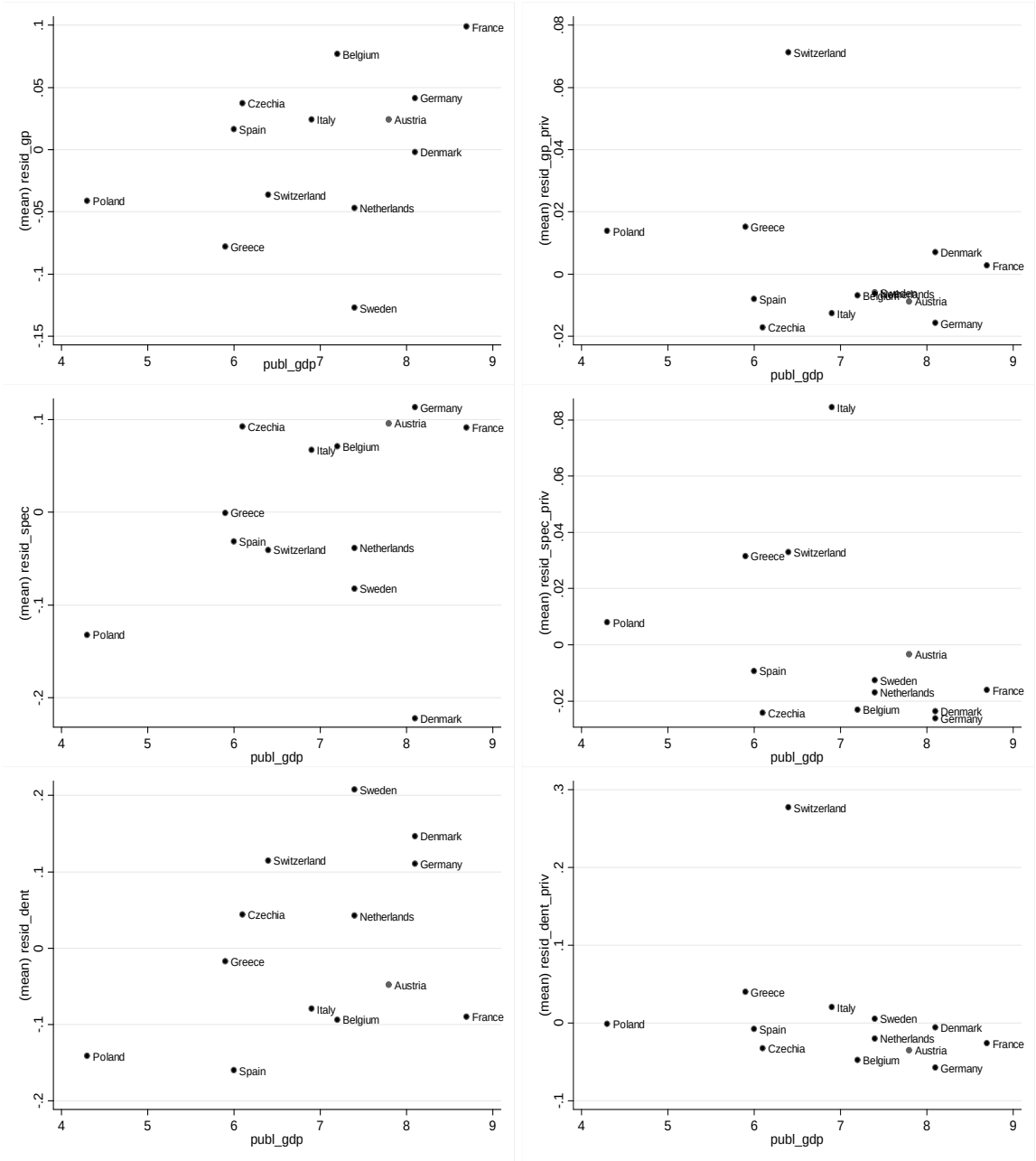








Public health expenditure relative to GDP and the unexplained part of outpatient care utilization (aggregate residuals)



3.A.4. OLS models of utilization

	GP		Specialist	
	Public	Private	Public	Private
age	0.001*	0.000	-0.004*	-0.001*
female	0.017*	0.000	0.028*	0.009*
mstat: w partner	-0.014	0.003	-0.042*	0.001
mstat: single	-0.010	0.003	-0.030*	-0.008*
log income	0.005	-0.001	0.010*	-0.002
log residence	0.001	0.000	0.000	0.001
log fin.wealth	0.000	0.000	0.005*	-0.001
edu: lower sec.	0.025	-0.005	0.087*	-0.009
edu: upper sec.	0.019	0.001	0.054*	0.000
edu: tertiary	-0.006	0.004	0.091*	-0.003
emp: employed	-0.047*	0.000	-0.088*	-0.004
emp: unemp.	-0.019	-0.003	-0.063*	-0.020*
emp: disabled	0.006	0.003	0.077*	0.003
emp: homem.	-0.025*	-0.005	-0.024	-0.008
self emp. ever	-0.042*	0.001	-0.029*	0.023*
area: suburbs	0.000	0.000	0.012	-0.015*
area: large town	-0.003	-0.001	-0.047*	-0.011*
area: small town	0.007	-0.001	-0.015	-0.015*
area: rural	0.003	0.000	-0.048*	-0.010
smoke: stopped	-0.016*	-0.002	0.030	-0.009*
smoke: yes	-0.067*	-0.003	-0.040	-0.011*
# illness	0.046*	0.001*	0.053*	0.009*
# ADL	-0.018*	0.001	-0.013*	0.000
# symptoms	0.012*	0.002*	0.029*	0.004*
GP copaym.	-0.055	0.014		
spec. copaym.			0.074	0.026
GP gatek.	-0.004	0.000	-0.084	0.040
GP/thousand	0.156*	-0.020		
phys/thousand			0.009	0.023
Constant	0.503*	0.024	0.299*	-0.040
R^2	0.088	0.007	0.097	0.027
Correlation	-0.271*		-0.179*	
Observations: 30,818				

* significant at 10%; * significant at 5%; * significant at 1%, based on clustered standard errors

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