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THE RELATIONSHIP BETWEEN BASELINE HEALTH AND LONGITUDINAL COSTS OF HOSPITAL USE

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SUMMARY

In this paper, we investigate the relationship between baseline health and costs of hospital use over a period of eight years. We combine cross-sectional survey data with information from the Dutch national hospital register. Four different indicators of health (self-perceived health, long-term impairments, ADL limitations and comorbidity) are considered. We find that for ages 50 to 70, differences in hospital costs between good health and bad health are substantial and persist during the whole time period. However, for higher ages expected hospital costs for individuals in bad health decline rapidly and become lower than those for people in good health after about six to seven years. The higher mortality rate among people in bad health is the primary cause here. Our results are confirmed for all four health indicators. We conclude that relying on better health to contain healthcare expenditures is too optimistic, and the interaction between health and mortality should be taken into account when projecting healthcare costs. Healthy ageing is important, but more for health gains than for cost savings. Copyright © 2010 John Wiley & Sons, Ltd.

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KEY WORDS: hospital costs; healthy ageing; longitudinal analysis

1. INTRODUCTION

The ageing of the population in most Western countries is an important issue in policy debate. The increase in the share of elderly in these countries, as a result of decreased fertility rates and increasing life expectancy, will put pressure on public finances. Healthcare use is highly correlated with age, therefore the budgetary effects of ageing are especially relevant in the health care sector. Because it has often been suggested that a part of the cost raising effects of ageing can be offset by an increase in general health, insight in the longitudinal relationship between health and costs of health care use is needed. The influence of health on costs of health care comprises two opposing components: better health is associated with lower costs per life year but also with additional costs associated with a higher remaining life expectancy. There is strong evidence of increasing trends in life expectancy, but the findings on trends in health and prevalence of chronic diseases are much less clear (De Hollander *et al.*, 2006; Fries, 2005; Luepker, 2006; Mackenbach *et al.*, 2008; Robine and Michel, 2004).

The influence of trends in health on costs of healthcare use are assessed in a number of studies (Michaud *et al.*, 2009; Manton *et al.*, 2007; Singer and Manton, 1998; Westerhout and Pellikaan, 2005). However, the relationship between health status, mortality and costs of healthcare use is seldom directly taken into account. Lubitz *et al.* (2003) do estimate this relationship using multistate lifetable techniques. They find that at 70 years of age, individuals with limitations in activities of daily living have

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a considerably lower life expectancy than individuals in good health, but the cumulative healthcare expenditures over their remaining life are almost equal. This result seems to indicate that better health will not necessarily lead to lower cost of healthcare use. Instead, the role of a longer life expectancy and postponement of costs to a later age may be more important.

This paper investigates the longitudinal relationship between health status and costs of hospital use in the Netherlands. We aim to provide the following contributions: First, we investigate the relationship between health and costs of hospital use over a time period of 8 years. We use survival analysis to relate initial health status to costs of hospital use in following yearly periods. In contrast, Lubitz *et al.* (2003) and Michaud *et al.* (2009) first relate costs of hospital use to current health status and then use Markov techniques to model transitions in health state. By directly estimating costs as a function of initial health, we avoid the possibly restrictive Markov assumption of duration independent transitions. There is evidence that the probability of returning to good health is smaller if the time spent in bad health is longer, and that transitions in health are indeed not independent of duration (Burchardt, 2000; Cai *et al.*, 2006; Crimmins *et al.*, 1994).

Second, we look at the relationship between health status and hospital costs for different age groups of people older than 50. Lubitz *et al.* (2003) focus on healthcare expenditures for individuals at the age of 70 years, but cost differences between health states at other ages might well show different results. The effect of initial health on mortality and hospital use, especially over a longer period of time, can be age- and sex dependent. For example, at higher ages initial health state might be less informative of future hospital costs, because the probability of becoming less healthy is higher than at lower ages.

Third, we estimate the relationship between health and hospital costs for different indicators of health (self-perceived health, long-term impairments, ADL and comorbidity). The relationship between health and costs may depend on the chosen measure. For instance, Cesari *et al.* (2008) find differences in performance between physical functioning and self-rated health in predicting mortality. The differences between indicators could also be age- and sex-specific and duration dependent.

We use eight years of Dutch cross-sectional health survey data and link this data to the Dutch National Medical Registration and the Causes of Death Statistics over the same period. This linkage allows us to estimate the relationship between health status, hospital use, and mortality over a maximum period of 8 years. We use a three-part model, modeling the probability of survival, the conditional probability of hospital use and the conditional costs of hospital use separately. Although there are a number of studies that use two- or three-part models for (semi-) continuous data, for example (Liu, 2009; Olsen and Schafer, 2001; Tian and Huang, 2007), to our knowledge this is the first implementation of such a model in a discrete survival context.

2. METHODS

2.1. Three-part model

We want to relate health status and background characteristics of an individual at a certain time t_0 to costs of hospital use in the following consecutive yearly periods after t_0. Let $h_{i,k}$ be the total costs of hospital care use of individual i during period $t_k \leq t < t_{k+1}$, where $k = 0,1,\ldots,K$ coincides with yearly time intervals. To relate $h_{i,k}$ to survival probability and health status, we start from a two-part model (Duan *et al.*, 1983) in which the probability of hospital use is modeled separately from the conditional costs of hospital use. This two-part model is extended with an additional part, modeling the probability of survival up to time t_k. This modeling strategy is used for two reasons: First, it allows us to separately identify the relationship between health and survival, health and probability of hospital use, and health and costs of hospital use. Second, modeling the probability of hospital use and costs of hospital use separately accounts for excess zeros: the number of people not using any hospital care during

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a particular year is so large that the observed number of zeros is many times higher than is consistent with, for example, a Poisson distribution.

The aim of our study is to estimate the overall influence of differences in health status on longitudinal hospital costs. Therefore, we use a marginal modeling framework (Lu *et al.*, 2004) for the three-part model. The resulting estimates provide population averaged effects, in the sense that they show the average difference in hospital costs between individuals in different health states. This is often the relevant viewpoint from a policy or societal perspective (Liu *et al.*, 2010). It can be expected, for example based on the well-known relationship between time to death and healthcare expenditures, that the different parts of the three-part model are correlated. The use of the marginal model implies that we do not model that correlation. An alternative model specification, which does take this inter-part correlation into account, would be a random effects model with correlated random effects between the different parts, for example applied by Liu (2009). As noted by Albert (2005), the marginal model and the correlated random effects model can yield different parameter estimates, when correlation between the parts indeed exists. Which model is correct again depends on the aim of the study. For example, the marginal model estimates of the third part of our three-part model for period k are estimates of the influence of health status on the conditional hospital costs for the individuals who actually went to the hospital in period k. Instead, the random effects estimates provide the effect of health status on conditional expenditures for an average individual from the total population. In accordance with the societal perspective of our study, the marginal model seems to be justified. For the same reason, we opt for the two-part model framework instead of a heckit model, because we consider the zeros to be actual outcomes and not censored 'potential' outcomes. As argued by Dow and Norton (2003), such an independent two-part model is often more appropriate for estimating real outcomes than inflated zero- or heckit models.

In the data, survival is observed in discrete time intervals. Therefore, we apply a discrete survival analysis approach to the three-part model. The first part of the model concerns the probability of being alive at time t_k. Let T_i be the duration of the time an individual is alive, then we use the following discrete time transition model (Cameron and Trivedi, 2006) for the probability of being alive up to time t_k:

$$\mathrm{P}(T_i \geq t_k | T_i \geq t_{k-1}, x_{i,t_k}) = F_1(x'_{i,t_k}\beta_{t_k}) \tag{1}$$

For F_1, we use the logistic cumulative density function. We condition the probability of being alive at t_k on being alive at time t_{k-1}, which means that we model the probability of surviving during period $t_{k-1} \leq t < t_k$. The parameters as well as the x vectors have a time subscript. This time dependence is discussed in Section 2.3. Equation (1) can be estimated by using a stacked data design: separate observations are constructed for each discrete time period during which individual i is alive and one observation for the period in which he or she dies. A dummy variable is added, indicating whether the individual i stays alive or dies during the period under consideration.

We formulate the second part of the model, the probability of hospital use, as

$$\mathrm{P}(h_{i,k} > 0 | T_i \geq t_k, x_{i,t_k}) = F_2(x'_{i,t_k}\beta_{t_k}) \tag{2}$$

The probability of hospital use during $t_k \leq t < t_{k+1}$ is expressed conditional on being alive up to time t_k. For F_2, we again use the logistic cdf. The third part of the model is the expected hospital use given any hospital use in period k. For this part, a general linear model is used:

$$\mathrm{E}(h_{i,k} | h_{i,k} > 0, x_{i,t_k}) = g(x'_{i,t_k}\beta_{t_k}) \tag{3}$$

The function $g(\cdot)$ links the linear relationship between the covariates $x'_{i,t_k}\beta_{t_k}$ to expected hospital use. The choice of this link function is discussed in Section 2.2.

The three parts of the model can be combined to get the unconditional expectation of costs of hospital use in period $t_k \leq t < t_{k+1}$:

$$\mathrm{E}(h_{i,k} | x_{i,t_k}) = \mathrm{E}(h_{i,k} | h_{i,k} > 0, x_{i,t_k}) \times \mathrm{P}(h_{i,k} > 0 | T_i \geq t_k, x_{i,t_k}) \times S_i(t_k, x_{i,t_k}). \tag{4}$$

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$S_i(t_k|x_i)$ is the survival function, the probability of surviving up to time t_k. This survival function is constructed by multiplying the probabilities from Equation (1) for $t = 0,1,\ldots t_k$ to obtain

$$S_i(t_k|x_{i,t_k}) = \prod_{j=1}^{k} \mathrm{P}(T_i \geq t_j | T_i \geq t_{j-1}, x_{i,t_j}) \tag{5}$$

Expected cumulative costs over longer discrete periods of time can be calculated by summing over the yearly periods. Let $H_{i,k}$ be the cumulative costs over the period 1 to k, then

$$\mathrm{E}(H_{i,k}|x_{i,t_k}) = \sum_{j=0}^{k} E(h_{i,k}|x_{i,t_k}) \tag{6}$$

To obtain confidence intervals for predicted survival, probability of hospital use, conditional- and unconditional costs of hospital use, we use bootstrapping. To preserve the correlation between longitudinal observations of the same individuals, we perform the bootstrap procedure with clustering observations on an individual level. The models for each indicator and their three separate parts are all estimated within the same sample. We use 1000 bootstrap runs.

2.2. Choosing the functional form

The third part of our model, concerning the conditional costs of hospital care in period k, is formulated as a general linear model (GLM). The reason for this formulation is that we expect the data to have thick right tails. Instead of log transforming the data, the GLM approach avoids transformation issues by directly modeling E(y) as a possibly nonlinear function of x. For notational convenience, let $y_{i,t_k} \equiv \mathrm{E}(h_{i,k}|h_{i,k} > 0, T_i \geq t_k)$ and $g^* = g^{-1}$ so that we can rewrite Equation (3) as

$$g^*(y_{i,t_k}|x_{i,t_k}) = x'_{i,t_k}\beta_{t_k} \tag{7}$$

The GLM approach requires the choice of the link function $g^*(\cdot)$ as well as a function for the variance of y_{i,t_k}. The link function determines the transformation of y_{i,t_k}. For example, the log-link models a linear relationship between $\log(y_{i,t_k})$ and $x_{i,tk}\beta_{tk}$:

$$g^*(y_{i,t_k}|x_{i,t_k}) = \log(y_{i,t_k}|x_{i,t_k}) = x'_{i,t_k}\beta_{t_k} \tag{8}$$

To determine the appropriate link function, we use a Box-Cox test. We limit our choice of variance functions to the class of power-proportional variance functions, which describe the relationship between $Var(y_i)$ and the mean as

$$Var(y_{i,t_k}) = y^m_{i,t_k} \tag{9}$$

where m is an integer. Different values of m coincide with well-known functional forms. For example, $m = 1$ is equivalent to a Poisson distribution and $m = 2$ is equivalent to a Gamma distribution. We use the modified Park test described by Manning and Mullahy (2001) to determine m.

2.3. Duration dependence

The formulation of the three-part model allows for time varying covariates as well as parameters. In case of the covariates, we use the values at time t_0. The reason for keeping the values at their initial level is that the model is forward looking or predictive: it estimates expected costs of hospital use in following periods based on information on current health status. We do correct for calendar year effects, caused by changes in budget constraints imposed by the government and other autonomous influences, by including calendar year dummies.

The effect of the health variables is allowed to change over time, by using duration-dependent parameters. The parameters of the other background variables are kept constant. In regard to the time

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dependence of the covariates and the parameters, the x-vector can be split up into three parts

$$x_{i,t_k}\beta_{t_k} = x^{a\prime}_{i,t_0}\beta^a_{t_k} + x^{b\prime}_{i,t_0}\beta^b + x^{c\prime}_{t_k}\beta^c \tag{10}$$

where the covariates x^a have time varying parameters $\beta^a_{t_k}$ and x^b have constant parameters β^b_{i,t_0}. The vector $x^c_{t_k}$ consists of the calendar year dummies.

The duration dependence of $\beta^a_{t_k}$ can be introduced by using a separate coefficient for each period. However, this would drastically increase the number of parameters in the models. To keep the model more parsimonious, we model duration dependence as an n-th order polynomial:

$$x'_{i,t_0}\beta_{t_k} = x'_{i,t_0}\beta_0 + \sum_{j=1}^{n} x'_{i,t_0}\beta_j k^j \tag{11}$$

The order of the polynomial n is determined by assessment of model fit, based on AIC and BIC values and Likelihood Ratio tests. Because a stacked data set is used, in which a separate individual observation is available for each period k, the inclusion of time-dependent parameters is straightforward.

3. DATA

3.1. General description of the data

The data used in this research are part of the Social Statistics Database (SSB)[1] of Statistics Netherlands (CBS). The SSB consists of a collection of several independent surveys and registrations. At the core of the SSB is the Municipal Population Registration (GBA), which contains basic information like date of birth and registered partners for everyone enlisted in a Dutch municipality. Databases in the SSB, can be linked to the GBA by means of an anonymized identification key. Using this key, it is possible to link information from different sources at an individual level. We use three data sources from the SSB: the Statistics Netherlands Integrated System of Social Surveys (POLS), the Dutch Causes of Death Statistics (DO) and the Dutch Hospital Discharge Register (LMR). The POLS survey consists of a basic survey and several modules, which cover a specific subject in more detail for different parts of the total POLS population. One of these modules is the POLS health survey. This health survey is a representative sample survey containing detailed information on health and healthcare use for approximately 10,000 individuals per year. We use the survey years 1997–2005. The Causes of Death Statistics is a register covering all deaths in the Netherlands. The Dutch Hospital Discharge Register (LMR) is provided by the Prismant healthcare services institute. All university and general hospitals and most specialized hospitals participate in the LMR. Therefore, the data set provides a nearly complete coverage of all hospital inpatient treatments in the Netherlands. All clinical and day admissions are registered based on a uniform registration system. The data include admission and discharge dates, and extensive treatment and diagnosis information on ICD-9 level.

We construct our data set by linking a particular POLS health survey year to consecutive years of the DO and LMR registers up to 2005. Linkage of POLS to the Causes of Death Statistics and LMR enables us to estimate mortality and hospital use for the POLS population in the years following the survey. For an individual from the 1997 survey, we can follow hospital use and mortality over a maximum of 9 years (1997–2005). However, for an individual from the 2005 survey, we can follow hospital use and mortality over a maximum of only 1 year. We define a period k as the k–1th year after the month an individual is interviewed in the POLS health survey. The POLS survey is organized in such a way that interview dates are equally spread over all months. Because we use yearly periods, only a small number of individuals can be followed over nine years (only the individuals interviewed in

[1]http://www.cbs.nl/nl-NL/menu/informatie/onderzoekers/ssb/ssb-info-medio-07.htm.

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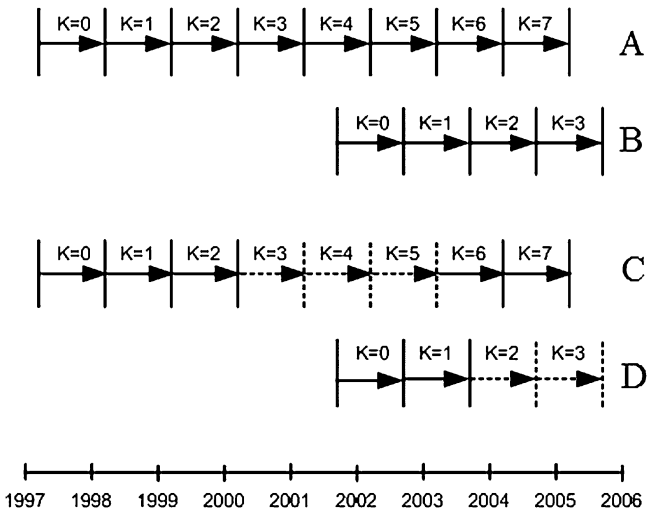

Figure 1. An illustration of the design of the data. Period k is defined as the kth year after the interview date. The two upper cases concern two individuals A and B. A is interviewed in POLS in January 1997 and his hospital use can therefore be observed for eight yearly periods, $k = 0,\ldots,7$. B is interviewed in June 2001, and his hospital use can be observed over four yearly periods $k = 0,\ldots,3$. The two lower cases concern individuals C and D who's hospital use is censored during a part of the observation period

January 1997). Therefore, we restrict our analysis to a maximum period of eight years. The way in which a period is defined is illustrated in Figure 1: the upper line shows individual A who is interviewed in February 1997 and who's hospital use can therefore be followed over eight yearly periods. As shown, the periods k generally do not coincide with calendar years. The second line in Figure 1 shows individual B who is interviewed in October 2001 and can therefore be tracked over four periods.

The LMR records do not contain a unique personal identification key, which would enable direct linkage to the POLS surveys. Instead, Statistics Netherlands provides a constructed identification key. This key is based on a linkage of records in the LMR to the Municipal Population Registration (GBA) by postal code, date of birth, gender and admission date. About 15% of the POLS population cannot be uniquely identified by this procedure. Because of removal to an area with another postal code or changing characteristics, identifiability can change over time. Individuals are only included in the estimation over the periods in which they are uniquely linkable. The procedure is illustrated by individuals C and D in the lower part of Figure 1. The two individuals are the same as for the lines on top, only they cannot be uniquely linked in all periods (indicated by the dotted lines).

Table I provides an overview of the population of the combined data set for each period. The population is categorized according to age and health status for the four indicators of health that are used in our subsequent analysis (Section 3.4). Age groups below 50 are not included in the table, because not all indicators of health are available for those groups. The number of people in each category is reported as well as the percentage of uniquely linkable individuals (in brackets). The probability of being uniquely linkable seems to increase with age, while the probability is rather stable over periods and between health states.

3.2. Censoring bias

Because of the different interview dates and the linkage procedure, a part of the data is censored: the hospital use of most individuals cannot be observed over the full evaluation period (eight years). If this censoring is not independent of hospital use, at least conditional on the x variables in the three-part

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Table I. Overview of the population of the POLS health surveys (1997–2005), according to age, period and health state (1 = best, 3 = worst), for four health indicators

Period	0			1			2			3			4			5			6			7		
Health	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Perceived health status																								
50–60	1387	4279	2512	1187	3629	2135	983	3010	1775	820	2487	1487	657	1966	1210	498	1433	877	340	921	561	180	493	293
	(0.85)	(0.86)	(0.87)	(0.86)	(0.86)	(0.87)	(0.86)	(0.86)	(0.87)	(0.87)	(0.86)	(0.88)	(0.87)	(0.87)	(0.89)	(0.88)	(0.87)	(0.90)	(0.89)	(0.89)	(0.91)	(0.90)	(0.89)	(0.93)
60–70	908	3143	2079	788	2712	1792	648	2279	1508	523	1901	1242	421	1531	1026	310	1156	791	204	785	538	104	421	312
	(0.91)	(0.91)	(0.89)	(0.91)	(0.90)	(0.89)	(0.91)	(0.92)	(0.89)	(0.90)	(0.92)	(0.90)	(0.91)	(0.92)	(0.91)	(0.91)	(0.92)	(0.91)	(0.90)	(0.93)	(0.91)	(0.89)	(0.95)	(0.90)
70–80	418	1920	2036	364	1637	1717	303	1346	1444	241	1109	1222	199	870	957	151	660	722	101	446	481	49	229	273
	(0.92)	(0.92)	(0.91)	(0.92)	(0.92)	(0.91)	(0.91)	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)	(0.90)	(0.93)	(0.93)	(0.90)	(0.94)	(0.94)	(0.92)	(0.94)	(0.95)	(0.89)	(0.96)	(0.95)
>80	119	614	735	99	528	613	78	436	525	64	352	447	53	279	353	38	207	258	34	134	170	20	74	85
	(0.96)	(0.94)	(0.96)	(0.96)	(0.95)	(0.96)	(0.96)	(0.96)	(0.97)	(0.98)	(0.98)	(0.97)	(0.96)	(0.99)	(0.98)	(0.97)	(0.97)	(1.00)	(0.97)	(0.98)	(1.00)	(0.91)	(0.97)	(1.00)
Long-term impairments																								
50–60	3586	1989	1140	3029	1660	953	2470	1387	755	2041	1176	643	1599	944	521	1202	696	382	798	447	244	421	227	140
	(0.86)	(0.86)	(0.87)	(0.86)	(0.85)	(0.87)	(0.86)	(0.86)	(0.87)	(0.87)	(0.88)	(0.88)	(0.87)	(0.88)	(0.89)	(0.88)	(0.88)	(0.88)	(0.90)	(0.89)	(0.88)	(0.91)	(0.90)	(0.93)
60–70	2351	1715	961	2004	1469	827	1644	1235	688	1344	1038	579	1059	859	478	816	649	369	572	430	249	316	219	141
	(0.91)	(0.90)	(0.90)	(0.91)	(0.90)	(0.89)	(0.92)	(0.90)	(0.90)	(0.92)	(0.91)	(0.90)	(0.92)	(0.92)	(0.90)	(0.93)	(0.92)	(0.89)	(0.93)	(0.93)	(0.88)	(0.94)	(0.92)	(0.88)
70–80	926	1200	1108	780	1018	919	646	826	758	531	680	645	412	541	505	316	413	393	216	285	262	110	153	135
	(0.92)	(0.92)	(0.90)	(0.92)	(0.92)	(0.90)	(0.92)	(0.92)	(0.90)	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)	(0.93)	(0.92)	(0.93)	(0.94)	(0.93)	(0.94)	(0.94)	(0.94)	(0.96)	(0.92)
>80	121	264	516	104	224	410	85	177	339	69	147	283	53	117	225	41	84	166	29	58	112	19	28	66
	(0.94)	(0.95)	(0.96)	(0.94)	(0.97)	(0.96)	(0.96)	(0.98)	(0.95)	(0.96)	(0.99)	(0.98)	(0.95)	(0.98)	(0.99)	(0.98)	(0.97)	(0.99)	(0.97)	(0.97)	(1.00)	(0.90)	(0.93)	(1.00)
ADL																								
50–60	3714	628	240	3145	526	204	2574	431	163	2134	348	131	1732	280	100	1292	193	77	847	127	50	454	79	28
	(0.87)	(0.87)	(0.89)	(0.87)	(0.86)	(0.88)	(0.87)	(0.87)	(0.90)	(0.88)	(0.89)	(0.90)	(0.89)	(0.91)	(0.88)	(0.89)	(0.91)	(0.90)	(0.91)	(0.92)	(0.91)	(0.92)	(0.93)	(0.90)
60–70	4608	1024	489	3972	901	411	3333	743	351	2755	616	289	2253	487	234	1719	353	181	1164	234	128	627	133	77
	(0.91)	(0.90)	(0.88)	(0.90)	(0.90)	(0.88)	(0.91)	(0.90)	(0.90)	(0.91)	(0.89)	(0.89)	(0.92)	(0.90)	(0.91)	(0.92)	(0.90)	(0.91)	(0.93)	(0.90)	(0.89)	(0.94)	(0.89)	(0.87)
70–80	2435	1095	835	2083	935	694	1734	772	583	1443	637	489	1147	499	377	874	370	286	607	226	193	308	129	113
	(0.92)	(0.91)	(0.90)	(0.92)	(0.91)	(0.90)	(0.92)	(0.92)	(0.91)	(0.92)	(0.93)	(0.92)	(0.92)	(0.93)	(0.93)	(0.93)	(0.93)	(0.93)	(0.94)	(0.94)	(0.95)	(0.95)	(0.95)	(0.94)
>80	480	428	545	411	358	460	335	305	391	283	250	325	220	197	265	160	143	197	115	86	135	65	44	69
	(0.96)	(0.94)	(0.95)	(0.97)	(0.94)	(0.96)	(0.97)	(0.96)	(0.96)	(0.99)	(0.97)	(0.97)	(0.99)	(0.97)	(0.98)	(0.99)	(0.97)	(0.99)	(0.97)	(1.00)	(1.00)	(0.94)	(1.00)	(1.00)
Comorbidity																								
50–60	3304	2007	1368	2789	1696	1112	2295	1387	875	1937	1153	696	1531	904	539	1165	667	379	770	421	249	400	233	142
	(0.85)	(0.87)	(0.87)	(0.85)	(0.87)	(0.87)	(0.85)	(0.88)	(0.88)	(0.86)	(0.88)	(0.88)	(0.86)	(0.89)	(0.89)	(0.87)	(0.89)	(0.90)	(0.88)	(0.90)	(0.89)	(0.89)	(0.91)	(0.93)
60–70	2174	1530	1247	1868	1301	1027	1552	1085	819	1292	870	666	1038	699	517	777	535	410	519	367	286	282	217	160
	(0.90)	(0.91)	(0.89)	(0.90)	(0.91)	(0.89)	(0.91)	(0.92)	(0.89)	(0.91)	(0.91)	(0.89)	(0.92)	(0.92)	(0.90)	(0.92)	(0.93)	(0.90)	(0.92)	(0.93)	(0.91)	(0.92)	(0.94)	(0.90)
70–80	1065	1006	1103	918	849	878	761	688	693	622	560	560	490	430	411	384	325	316	271	222	208	132	124	118
	(0.92)	(0.92)	(0.91)	(0.92)	(0.93)	(0.92)	(0.92)	(0.93)	(0.92)	(0.91)	(0.93)	(0.93)	(0.92)	(0.93)	(0.92)	(0.92)	(0.95)	(0.93)	(0.93)	(0.94)	(0.93)	(0.94)	(0.95)	(0.94)
>80	275	276	318	228	229	248	187	189	188	162	149	149	125	114	116	94	80	88	65	61	54	35	37	30
	(0.96)	(0.96)	(0.96)	(0.97)	(0.96)	(0.96)	(0.96)	(0.97)	(0.97)	(0.97)	(0.99)	(0.97)	(0.96)	(0.97)	(1.00)	(0.97)	(0.99)	(1.00)	(0.97)	(1.00)	(1.00)	(0.95)	(0.97)	(1.00)

The numbers between brackets indicate the percentage of the sample that can be linked to the Dutch hospital register.

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model, it may lead to biased estimates. It has often been argued that in modeling medical cost data the independence assumption does not hold (Başer *et al.*, 2006; Lin, 2003). The argument is that individuals who survive during the whole evaluation period are at risk of being censored during a longer period of time than individuals who die during the evaluation period. Because hospital costs are known to be higher for deceased than for survivors (Zweifel *et al.*, 1999), ignoring this difference may bias cost estimates upward.

The first cause of censoring, the different interview dates, does not lead to estimation bias. As illustrated by Figure 1, individuals are only included for the yearly time intervals that end before 2006. For example, if individual B would die in November 2005, his observation for $k = 4$ would not be included. Since censoring in this case is determined only by interview date, it is random and therefore does not influence the estimates. In contrast, the linkage procedure could lead to estimation bias: individuals who die during a period $t_k \leq t < t_{k+1}$ have a higher probability of being linked to the LMR than individuals who survive up to time t_{k+1}. The probability of unique linkage is known to depend on characteristics like age, income and ethnicity (De Bruin *et al.*, 2003), but because the model includes socioeconomic background variables this is not a problem. However, it is not unlikely that the probability of linkage is also dependent on survival probability. Therefore, we test whether individuals who die during period k have a higher probability of being uniquely linked than survivors.

3.3. Assigning costs

Costs per admission are not supplied in the data set, but are calculated by using data from the Dutch Costs of Illness Study (Slobbe *et al.*, 2006). In this general cost of illness study, total healthcare expenditure are assigned to diseases and patient characteristics. For hospital expenditure, a combined top–down and bottom–up approach is used. Total hospital expenditure is known from national health accounts and can be broken down to inpatient and ambulatory care, respectively, using data from the Dutch hospital budget system. In this paper, we focus on inpatient care including all clinical procedures and day cases, comprising 60% of total hospital expenditure. Costs per admission are split up into two parts: intervention costs and all other costs associated with hospital stay. As all interventions are registered in the LMR in ICD-9 format, intervention costs per patient can be calculated using the detailed remuneration schemes of the Dutch hospital payment system. This scheme provides for each intervention all relevant doctor's fees and the hospital's reimbursement for associated costs of, among others, equipment, materials and personnel. All other costs of hospital stay, like nursing and accommodation costs, are calculated on a daily basis, using average per diem costs. Costs are aggregated per admission.

3.4. Indicators of health

We use four different measures of health status: self-perceived health status, long-term impairments, limitations in Activities of Daily Living (ADL), and comorbidity. For each measure, we construct an indicator with three levels based on associated questions in POLS. The indicator for self-perceived health status is based on one question in which individuals are asked to describe their own health in terms of five answer categories. However, in 2001, the definition of the answer categories has been changed. This change causes a break in the trends for the lowest three categories. Therefore, we combine the lowest three categories into one new category that does not show a trend break (Botterweck *et al.*, 2003). The classification of long-term impairments is based on parts of an OECD questionnaire included in the POLS survey. The questions and constructed indicators for each measure are reported in Table II.

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Table II. Indicators of health in POLS: questions, answers and elements of the constructed categories used

Measure	Questions	Answers	Levels
Self-perceived health	How would you describe your own health?	very good good less than good	1. very good 2. good 3. less than good
Long-term impairments	Can you follow a conversation in a group of 3 or more persons? have a conversation with one person? read the small print in the newspaper? recognize a face at a distance of four meters? carry an object of 5 kilograms for 10 meters? bend down and pick up something from the floor? walk 400 meters without resting?	yes, without difficulty with minor difficulty with major difficulty unable to do	1. yes, without difficulty 2. at least one minor difficulty 3. at least one major difficulty
ADL limitations	Can you eat and drink? get up from a sitting position? get in- and out of bed? dress and undress? transfer to another room on the same floor? climb up and down the stairs? enter and leave the house? transfer outdoors? wash face and hands? bath?	yes, without difficulty with minor difficulty with major difficulty only with aid	1. yes, without difficulty 2. at least one minor difficulty 3. at least one major difficulty
Comorbidity	Occurrence in the last 12 months asthma diabetes rheumatism migraine high blood pressure cancer stroke back disorder heart disorder intestines disorder arthrosis		1. no disease 2. one disease 3. more than one disease

4. RESULTS

The three-part model for the relationship between health and costs of hospital use is estimated for each indicator of health separately. The same set of explanatory variables is used for all indicators and for each part of the three-part model. The relationship between sex, age and health is introduced as a three-way interaction effect, using dummies for each three-way category. The parameters of these three-way interactions are duration dependent. The other included covariates are a series of calendar year dummies and a series of dummy variables for the highest attained education level. A dummy variable for ethnicity was dropped, due to a lack of significance. A logit model, including the same set of variables as the three-part model and a dummy for dying, has been used to test whether linkage to the hospital register during a certain period depends on surviving that period. No significant effect of survival on linkage probability has been found. Therefore, we decide not to use correction weights in the three-part models.

Results from the Box-Cox test for different specifications of the model indicate that the log-link provides the best fit to the data. To determine the functional form of the third part, the GLM model for conditional costs of hospital use, we perform the modified Park test. The test indicates a quadratic relationship between mean and variance, equivalent to the Gamma family, for all indicators of health. Assessments of fit based on AIC and BIC criteria and likelihood ratio tests show a better fit for the models with linear duration dependence than constant duration dependence. The results are less clear

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on the choice between linear and quadratic duration dependence. Especially in the first part of the model, a quadratic duration dependence seems to provide a somewhat better fit than linear dependence. To keep the models parsimonious and comparable, between parts and between indicators of health, we use linear duration dependence for all models. The regression results for each health indicator, including the values of the information criteria and the LR tests, are reported in Appendix A. In each table, the coefficients and p-values for all the three parts of the model are shown. The three-way dummies have two coefficients: one for the time constant, or baseline effect, and one for the time varying effect. For age, we use ten-year groups from 50 onwards.

We use the estimated parameters in Appendix A to make predictions of survival, probability of hospital use, conditional- and unconditional costs of hospital use. Separate predictions are made for each combination of sex, age and health, while keeping the other background variables at their baseline level (education level is low and evaluation year is 1997). Figures 2–5 show the predictions and bootstrapped 95% confidence intervals for self-perceived health status. Figure 2 shows the survival up to period k, which is constructed by multiplying the survival probabilities for each period up to k as described in Equation (5). Survival is consistently lower for individuals in bad health compared with the individuals with the same age and sex in good health. The graphs also show a negative correlation between age and survival, and lower survival for men than for women with the same age and health.

The predicted probability of hospital use in period k conditional on being alive at the start of period k is shown in Figure 3. The probability of hospital use in the first period increases with worsening health state. The initial probability of hospital use also shows a correlation with age, but the sex differences are limited. Considering the time patterns, the differences in probability of hospital use seem to be rather constant over time for the age groups 50–60 and 60–70 years. For the two oldest age groups, there is convergence in probability of hospital use over time. For men older than 80 and women older than 70,

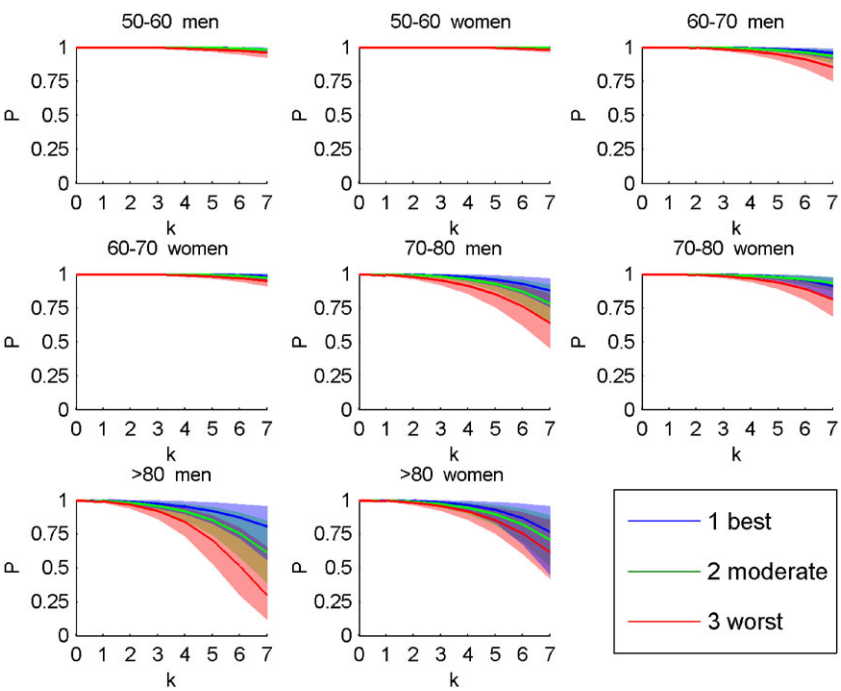

Figure 2. Part 1 for perceived health status: predicted probability of being alive in a period k and bootstrapped 95% confidence intervals

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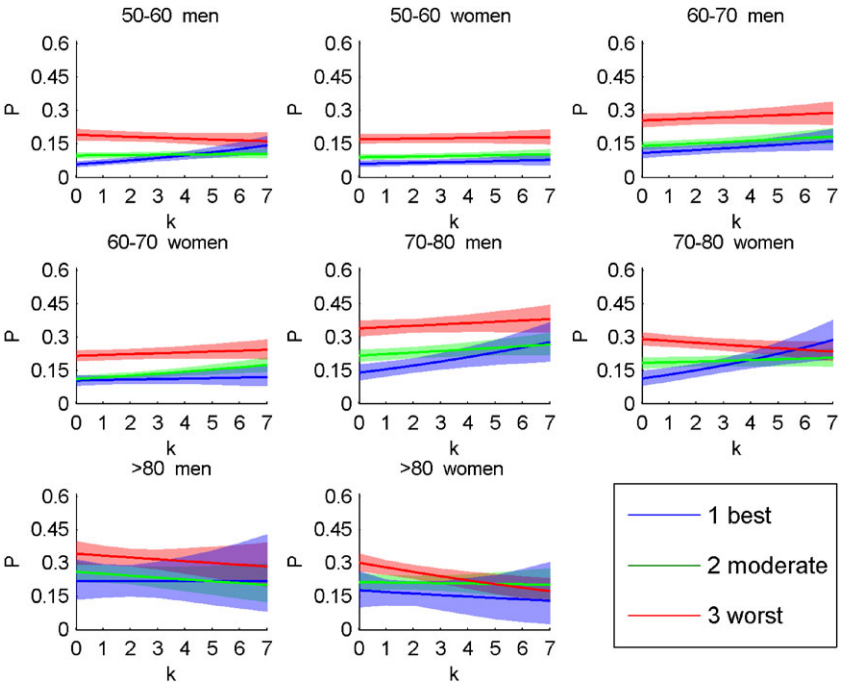

Figure 3. Part 2 for perceived health status: predicted probability of any hospital use in a period k given alive in period k and bootstrapped 95% confidence intervals, by health state

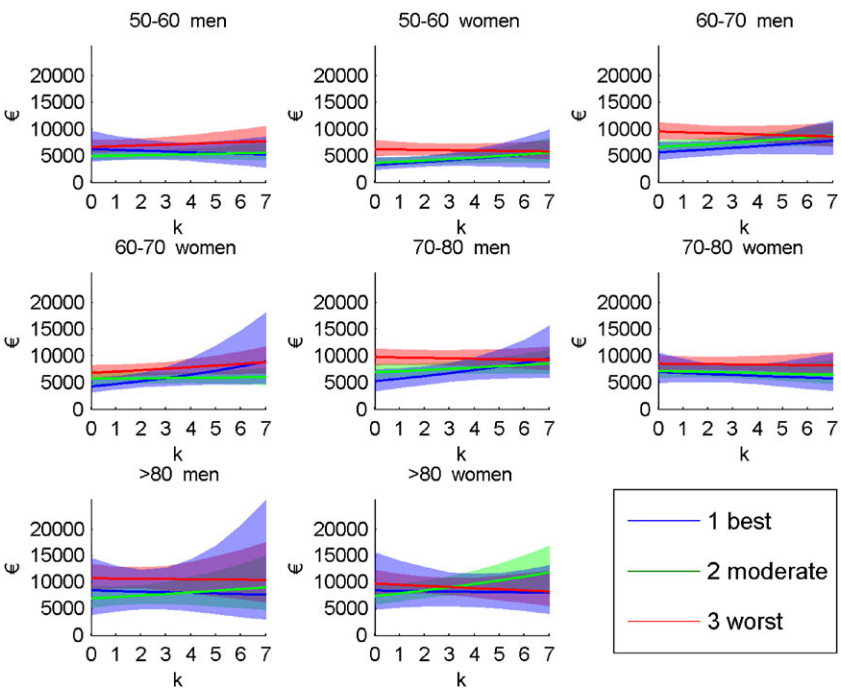

Figure 4. Part 3 for perceived health status: predicted costs (euro) of hospital use in a period k given any hospital use in period k and bootstrapped 95% confidence interval, by health state

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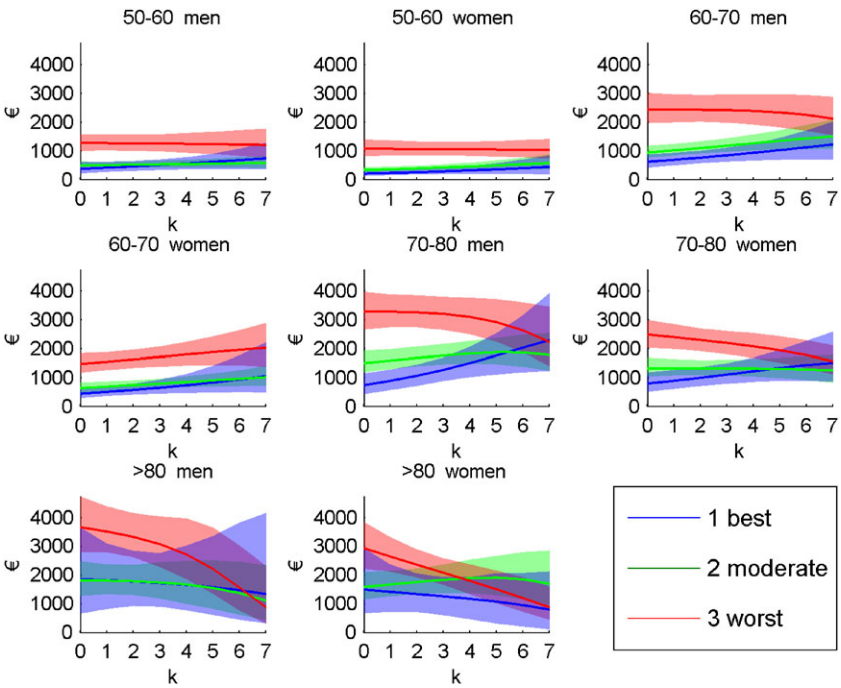

Figure 5. Total for perceived health status: predicted costs (euro) of hospital use in a period k, by health state. Bootstrapped 95% confidence intervals

the probability of hospital use given initial bad perceived health declines over time, whereas the probability of hospital use given excellent health between 70–80 increases.

The costs of hospital use conditional on having any hospital use in period k, displayed in Figure 4, are higher for individuals with bad perceived health than individuals in good perceived health. For bad health in the young age groups, the conditional costs of hospital use show a sharp increase over time. At higher ages, the differences again show some convergence over time.

Multiplying survival, probability of use and conditional costs of hospital use as in Equation (4), yields the unconditional predictions of hospital use for each period k in Figure 5. It appears that the levels of expected hospital use in the first period increase with age, but the relative differences between bad health and good health remain relatively stable. At lower ages, the differences in expected hospital use are quite persistent over time. At higher ages, the expected hospital use for individuals in bad health decreases over time, whereas the hospital use for individuals in good and excellent health remains stable or even increases. As a result, for the highest male age group, the expected hospital use is higher for individuals in excellent health than individuals in bad health in 6 and 7 years after measurement of health.

For the other three indicators, being long-term limitations, limitations in activities in daily living and comorbidity, we only show the unconditional predictions in Figures 6–8. The same general patterns seem to occur for all indicators. For younger age groups, differences in costs between good and bad health are relatively stable over time. For older age groups, the expected costs of individuals in bad and in good health converge over time. In case of major long-term impairments, shown in Figure 6, this convergence is already visible for men between 60 and 70 years. In contrast, for women this convergence only occurs for the oldest age group. The costs of men between 50 and 60 years with major ADL limitations (Figure 7) show an increasing time pattern, whereas the costs for women with the same age

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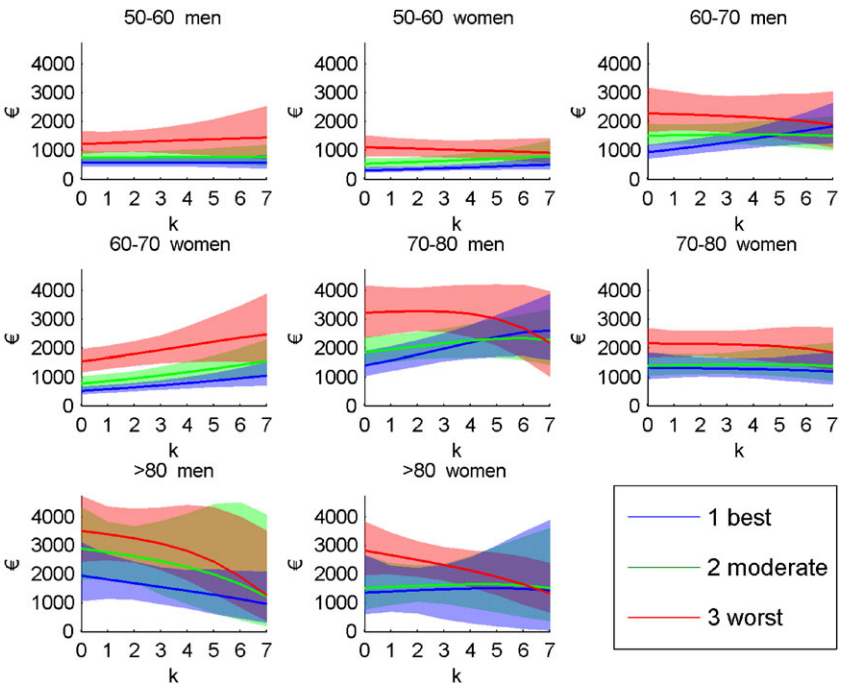

Figure 6. Predicted costs (euro) of hospital use, long-term impairments, by health state. Bootstrapped 95% confidence intervals

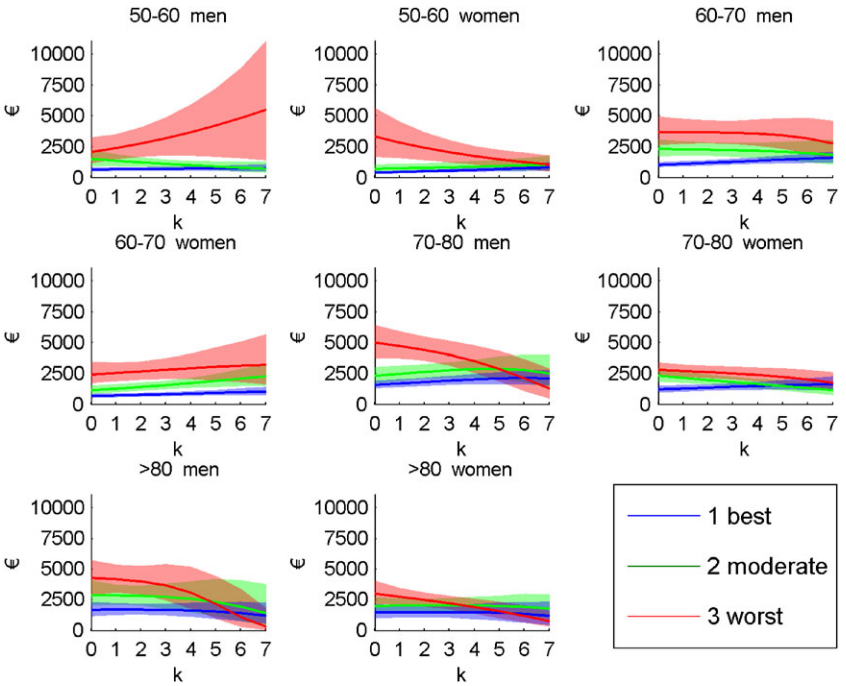

Figure 7. Predicted costs (euro) of hospital use, ADL limitations, by health state. Bootstrapped 95% confidence intervals

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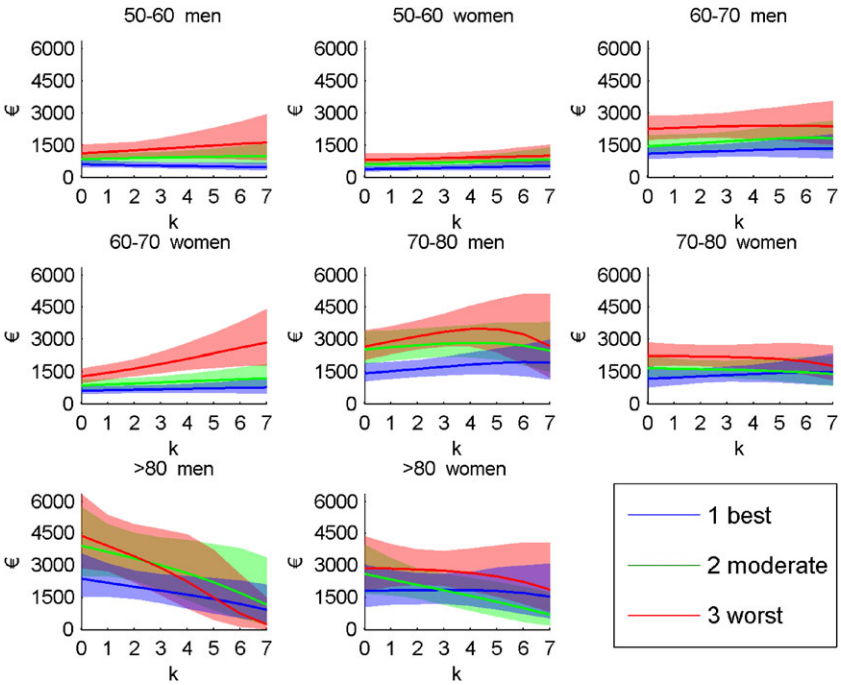

Figure 8. Predicted costs (euro) of hospital use, comorbidity, by health state. Bootstrapped 95% confidence intervals

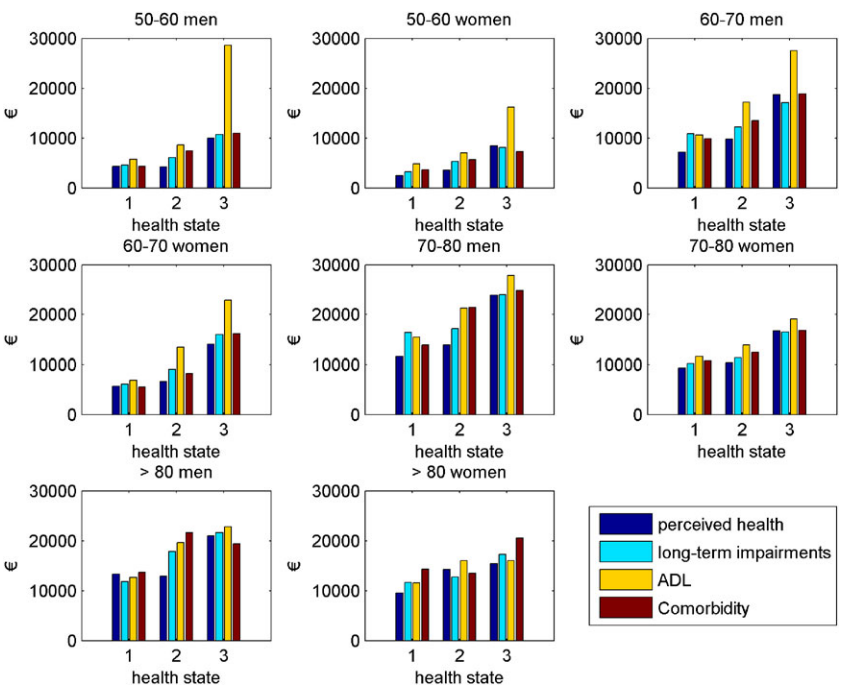

Figure 9. Cumulative costs (euro) of hospital use over eight periods by different levels of health (1, 2 and 3) for different measures of health status. The different health states are described in Table II

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Table III. Differences in cumulative costs (€), over the first 8 years after the measurement of health state, between the worst health state and best health state

		Men			Women		
Indicator	Age	Total	Const. surv.	Survival	Total	Const. surv.	Survival
Perc. health	50–60	5604	5699	95	5930	5969	39
	60–70	11 537	12 162	625	8290	8498	208
	70–80	12 313	14 521	2208	7430	7937	508
	>80	**7693**	11 623	3929	5875	6608	**733**
Long-term imp.	50–60	6117	6178	**61**	4898	4921	**23**
	60–70	6180	6437	256	9865	10 017	152
	70–80	7614	9591	1978	6274	6713	438
	>80	9785	12 214	2429	**5670**	**6571**	**902**
ADL	50–60	22 922	23 580	**657**	11 319	11 478	160
	60–70	16 909	18 936	2026	15 972	16 599	627
	70–80	12 395	17 027	4632	7444	8322	879
	>80	10 166	16 785	6619	4454	5815	1361
Comorbidity	50–60	6663	6750	**87**	3649	3661	**12**
	60–70	8965	9310	345	10 577	10 742	**165**
	70–80	10 927	14 276	3348	6025	6444	420
	>80	**5761**	10 047	4287	**6262**	**7112**	**849**

The total difference (total) is split up into a part due to difference in intensity, keeping survival at the good health level (const. surv), and the difference due to the lower survival for bad health (survival). Numbers in bold are not significantly different from zero (5% significance level, bootstrapped).

show a declining pattern. The high uncertainty surrounding the prediction for men could suggest an outlier effect. For the other age groups, the initial differences between no impairments and major impairments are larger for men than for women. The expected costs of individuals with major impairments in the two oldest age groups are lower than the costs of individuals without initial impairments, after 6–7 years. The costs of hospital use for comorbidity, in Figure 8, again show the same converging pattern over time for the oldest age group.

The expected costs over all eight periods (cumulative costs) are shown in Figure 9. For the age groups of 50–60 and 60–70 years, the cumulative costs rise with worsening health for each indicator. For the older age groups, the cumulative costs for people in bad health are still higher than for people in good health, but the pattern is less strong. For instance, in the case of comorbidity, the relative differences are much smaller at older ages compared with the differences at younger ages. The cumulative costs for men older than 80 years with moderate perceived health are lower than the costs for men of the same age with excellent health. The cumulative costs for women in the highest age category are also higher with no comorbidity than with moderate comorbidity. Women older than 80 years with severe ADL limitations have lower cumulative costs than women with only moderate ADL limitations.

Table III shows the difference in cumulative costs between excellent and bad health, for each indicator and age- and sex group. Bootstrapped 5% significance levels are also provided. The differences in cumulative costs increase with age for men in case of long-term impairments, and decrease for men in case of ADL. All the other groups first show an increase in cumulative costs between 50 and 70/80 and then a decline. In four cases of the oldest age group the difference in cumulative costs is not significantly different from zero at a 5% significance level: self-perceived health and comorbidity for men, and long-term impairments and comorbidity for women. Table III also shows which part of the cost difference is due to increased intensity (where survival is kept at the level of good health), and which part is due to the lower survival probability of individuals in bad health. The diminishing effect of survival on cost differences increases with age, and is larger for men than for women.

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5. DISCUSSION

In this paper, we have analyzed the longitudinal relationship between health status and costs of hospital use in the Netherlands. Initial health status has been related to costs of hospital use in the following 8 years using a three-part model, estimating survival, probability of hospital use and costs of hospital use separately. We have estimated costs using four different indicators of health and several age groups. Our main finding is that for age groups up to 70 years, bad health leads to higher costs of hospital use and the difference between bad and good health is generally persistent over an 8-year period. For higher age groups, however, a different pattern arises: mostly due to higher mortality, the expected costs of individuals in bad health show a decreasing pattern, resulting in lower expected costs after 6–8 years compared with individuals in good health. This result is found for all four indicators of health.

The effect of health in the three part models is modeled with a linear time dependency. The regression results in Appendix A show that not all time-dependent parameter are significant (at a 5% level). Because one of our goals is to explicitly describe the time dependency of initial health on hospital costs, we decided to keep the not significant time-dependent parameters in the models. The most striking example of duration dependence is the effect of excellent perceived health on probability of hospital use, shown in Figure 3. For the ages of 50–80 years, the probability of hospital use shows an increase over time for individuals in excellent health. There seems to be a postponement effect: in the long-run better health does not lead to lower hospital use, but merely to a postponement of hospital use to a later period in time.

The results on age effects are in line with what is expected: older age leads to higher mortality, higher conditional probability of hospital use, and higher conditional costs of hospital use. Considering the cumulative costs over 8 years, the generally higher costs for ages 60–70 years compared with ages 50–60 indicate that between ages 50 and 70 the effect of mortality on costs is relatively small. But after age 70, the cumulative costs are more or less constant, implying that the age effect on increasing costs is mitigated by the age effect on mortality. As shown by the split up of costs due to difference in intensity and differences in survival, the lower survival probability of people in bad health has a large lowering influence on the costs difference with people in good health at higher ages. This effect is stronger for men than for women, due to the greater differences in survival between health states for men. Interestingly, the higher life expectancy of women compared with men does not lead to higher cumulative costs.

The general patterns are the same for the different indicators of health, but the results also show some relevant differences. At ages 50–70, the differences in cumulative costs between best and worst health state are considerably higher for ADL than for the other indicators, due to the high costs associated with major ADL impairments. Even at older ages, major ADL impairments are associated with higher costs than the worst health states of the other indicators. However, as major ADL impairments are also associated with higher mortality at older ages, the difference in cumulative costs between best and worst health state is much more similar to the other indicators. This result shows the importance of choice of health indicator and the interactive effect of health and age on healthcare costs as well as survival.

We have opted for the use of a marginal model framework instead of a random effects model, in which correlation between the different parts of the models is explicitly modeled (Liu, 2009; Liu *et al*., 2010). The marginal model was chosen because of the interest in the population averaged effects. As noted by Liu *et al*. (2010), random effects models can also be used to estimate population average effects by averaging over the distribution of the random effects. In case the individual effects indeed follow the distribution specified by the correlated random effects model, this model might yield more efficient population averaged estimates. However, in general the marginal model seems to be more robust to specification errors.

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Although costs of hospital use are observed over all periods, health status is only observed at the beginning of the first period. As a result, the individual costs of hospital use cannot be directly related to changes in health status over time. The declining patterns of expected costs of low health at older ages seem to indicate that the expected hospital costs over remaining lifetime may well be lower for individuals in bad health than individuals in good health. Therefore, relating hospital costs directly to changes in health status over time and simulating costs over the remaining lifetime seem to be fruitful future extensions. At least, when duration dependence in transition probabilities is accurately dealt with.

This paper is limited to costs of hospital use. Hospital care is an important part of health care, but for other parts of care different results may be found. Especially relevant at old ages is institutional or long-term care, where substitution with hospital care may occur. The trade off, in terms of costs, between annual costs and life expectancy, will most likely also be present in other parts of the healthcare sector. However, the relative influence of these opposing components may be different from that in hospital care. For example, in a cross-sectional study, De Meijer *et al.* (2009) find that after controlling for disability, age is still a significant determinant of long-term care. This might suggest that the influence of longer life expectancy is even larger in long-term care than in hospital care. However, to assess whether this is indeed the case, longitudinal research on the relationship between health status and long-term care costs is needed.

6. CONCLUSIONS

The ageing of the population will put pressure on healthcare expenditures. The improvement of health status is often seen as an instrument to contain the costs of health care. Therefore, insight into the longitudinal relationship between health and costs of healthcare use is necessary. In this paper, we have investigated the relationship between different indicators of health and costs of hospital use in the Netherlands over a period of 8 years. We have found that for the relatively younger age groups, between ages 50 and 70 years, baseline good health is persistently associated with low expected costs of hospital use in comparison with bad health over an 8-year period. At higher ages, the initial lowering effect of good health on costs seems to be counteracted over time by lower mortality.

Improvement of public health is an important policy goal in itself. However, this study suggests that health improvement of the elderly does not necessarily lead to containment of healthcare costs. Although specific health improvements can be cost effective, counting on general trends in health to lower long-term costs of health care is too optimistic. Interaction between health and mortality, and possible postponement of costs, should be taken into account when making projections of future costs of health care.

APPENDIX A: REGRESSION TABLES

The regression results for each health indicator are reported in Tables AI–AIV.

Table AI. Regression results of the three-part model for perceived health status, coefficients and p-values

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
t-independent								
50–60	M	2	−0.48	0.48	0.55	0.00	−0.24	0.18
50–60	M	3	−2.04	0.00	1.32	0.00	0.06	0.74
50–60	W	1	−0.46	0.60	0.04	0.81	−0.63	0.01
50–60	W	2	1.38	0.11	0.46	0.00	−0.54	0.00
50–60	W	3	−1.14	0.10	1.19	0.00	−0.01	0.97
60–70	M	1	−1.37	0.07	0.67	0.00	−0.11	0.62
60–70	M	2	−1.53	0.02	0.96	0.00	0.06	0.75
60–70	M	3	−2.37	0.00	1.69	0.00	0.42	0.02
60–70	W	1	1.11	0.39	0.61	0.00	−0.38	0.11

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Table AI. *Continued*

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
60–70	W	2	−0.37	0.60	0.68	0.00	−0.09	0.64
60–70	W	3	−1.78	0.01	1.47	0.00	0.08	0.63
70–80	M	1	−2.10	0.01	0.94	0.00	−0.17	0.49
70–80	M	2	−2.37	0.00	1.47	0.00	0.10	0.57
70–80	M	3	−3.38	0.00	2.09	0.00	0.43	0.01
70–80	W	1	−0.96	0.28	0.70	0.00	0.11	0.70
70–80	W	2	−1.87	0.00	1.27	0.00	0.14	0.44
70–80	W	3	−2.30	0.00	1.87	0.00	0.31	0.07
>80	M	1	−3.00	0.00	1.50	0.00	0.30	0.42
>80	M	2	−3.15	0.00	1.72	0.00	0.11	0.63
>80	M	3	−3.47	0.00	2.11	0.00	0.54	0.01
>80	W	1	−2.13	0.02	1.23	0.00	0.30	0.41
>80	W	2	−2.74	0.00	1.46	0.00	0.17	0.42
>80	W	3	−3.17	0.00	1.92	0.00	0.44	0.02
t-dependent								
50–60	M	1	−0.55	0.00	0.14	0.00	−0.03	0.55
50–60	M	2	−0.47	0.00	0.01	0.49	0.02	0.52
50–60	M	3	−0.30	0.00	−0.03	0.14	0.02	0.39
50–60	W	1	−0.29	0.05	0.04	0.28	0.07	0.15
50–60	W	2	−0.63	0.00	0.02	0.24	0.06	0.02
50–60	W	3	−0.35	0.00	0.01	0.60	−0.01	0.68
60–70	M	1	−0.44	0.00	0.07	0.04	0.05	0.30
60–70	M	2	−0.49	0.00	0.04	0.01	0.04	0.08
60–70	M	3	−0.48	0.00	0.02	0.18	−0.01	0.54
60–70	W	1	−0.72	0.00	0.02	0.57	0.11	0.09
60–70	W	2	−0.55	0.00	0.08	0.00	0.01	0.81
60–70	W	3	−0.40	0.00	0.02	0.20	0.04	0.12
70–80	M	1	−0.50	0.00	0.12	0.00	0.08	0.14
70–80	M	2	−0.56	0.00	0.04	0.06	0.03	0.28
70–80	M	3	−0.49	0.00	0.03	0.21	−0.01	0.77
70–80	W	1	−0.64	0.00	0.16	0.00	−0.03	0.71
70–80	W	2	−0.43	0.00	0.02	0.29	−0.01	0.60
70–80	W	3	−0.54	0.00	−0.04	0.02	−0.01	0.83
>80	M	1	−0.43	0.00	0.00	0.98	−0.01	0.90
>80	M	2	−0.55	0.00	−0.05	0.28	0.04	0.57
>80	M	3	−0.67	0.00	−0.04	0.38	0.00	0.95
>80	W	1	−0.62	0.00	−0.05	0.57	−0.01	0.95
>80	W	2	−0.56	0.00	−0.01	0.80	0.07	0.17
>80	W	3	−0.54	0.00	−0.10	0.00	−0.02	0.59
1998					−0.08	0.25	0.16	0.10
1999			−0.96	0.01	−0.10	0.13	0.07	0.46
2000			−1.44	0.00	−0.05	0.41	0.01	0.92
2001			−1.52	0.00	−0.03	0.58	−0.10	0.24
2002			−1.64	0.00	0.06	0.33	−0.14	0.09
2003			−1.81	0.00	0.12	0.05	−0.14	0.09
2004			−1.85	0.00	0.21	0.00	−0.26	0.00
2005			−1.00	0.21	−0.03	0.83	−0.29	0.14
LS			0.29	0.00	0.01	0.70	−0.05	0.14
HS			0.22	0.00	−0.01	0.67	0.01	0.85
H			0.43	0.00	−0.07	0.02	−0.20	0.00
c			8.47	0.00	−2.76	0.00	8.75	0.00
No. of observations				92 680		83 010		14 684
d.f.				58		59		59
Pseudo R^2				0.258		0.043		
Log-likelihood				−8830		−37 076		−142 511
AIC				17 775		74 270		285 140
BIC				18 323		74 820		285 588

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Table AI. *Continued*

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
LR constant vs linear			χ^2_{24} (2017)		χ^2_{24} (102)		χ^2_{24} (60)	
LR linear vs quadratic			χ^2_{24} (202)		χ^2_{24} (23)		χ^2_{24} (43)	

Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period k. Part 3: Gamma model for the costs of hospital use in period k conditional on going to the hospital in period k. Health: 1 excellent health, 2 good health, 3 less than good health. Likelihood ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence.

Table AII. Regression results of the three-part model for long-term impairments, coefficients and p-values

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
t-independent								
50–60	M	2	−0.20	0.66	0.43	0.00	−0.11	0.40
50–60	M	3	−0.46	0.37	0.72	0.00	0.13	0.37
50–60	W	1	1.25	0.03	−0.11	0.20	−0.52	0.00
50–60	W	2	1.04	0.14	0.23	0.01	−0.27	0.03
50–60	W	3	0.48	0.42	0.68	0.00	0.06	0.63
60–70	M	1	−0.71	0.05	0.42	0.00	0.11	0.33
60–70	M	2	−0.70	0.07	0.75	0.00	0.31	0.01
60–70	M	3	−1.17	0.01	1.13	0.00	0.43	0.00
60–70	W	1	0.21	0.66	0.26	0.00	−0.33	0.01
60–70	W	2	0.67	0.23	0.39	0.00	−0.05	0.68
60–70	W	3	−0.11	0.82	0.94	0.00	0.18	0.17
70–80	M	1	−1.28	0.00	0.88	0.00	0.13	0.34
70–80	M	2	−1.29	0.00	1.10	0.00	0.24	0.05
70–80	M	3	−2.19	0.00	1.50	0.00	0.51	0.00
70–80	W	1	−0.70	0.17	0.59	0.00	0.32	0.05
70–80	W	2	−0.18	0.69	0.96	0.00	0.06	0.64
70–80	W	3	−0.95	0.01	1.20	0.00	0.31	0.01
>80	M	1	−1.94	0.00	1.31	0.00	0.14	0.60
>80	M	2	−1.64	0.00	1.53	0.00	0.38	0.05
>80	M	3	−2.22	0.00	1.57	0.00	0.54	0.00
>80	W	1	−1.01	0.26	0.90	0.00	0.09	0.79
>80	W	2	−1.35	0.02	0.85	0.00	0.24	0.36
>80	W	3	−2.18	0.00	1.26	0.00	0.55	0.00
t-dependent								
50–60	M	1	−0.36	0.00	0.02	0.35	−0.02	0.54
50–60	M	2	−0.41	0.00	−0.01	0.64	0.02	0.63
50–60	M	3	−0.41	0.00	−0.01	0.76	0.04	0.33
50–60	W	1	−0.51	0.00	0.03	0.17	0.05	0.10
50–60	W	2	−0.36	0.01	0.01	0.58	0.05	0.14
50–60	W	3	−0.48	0.00	0.02	0.54	−0.04	0.29
60–70	M	1	−0.46	0.00	0.06	0.00	0.06	0.02
60–70	M	2	−0.51	0.00	0.03	0.15	−0.01	0.64
60–70	M	3	−0.49	0.00	−0.02	0.54	0.00	0.93
60–70	W	1	−0.50	0.00	0.06	0.01	0.06	0.06
60–70	W	2	−0.58	0.00	0.08	0.00	0.04	0.17
60–70	W	3	−0.57	0.00	0.04	0.10	0.05	0.15
70–80	M	1	−0.57	0.00	0.08	0.00	0.06	0.11
70–80	M	2	−0.56	0.00	0.04	0.10	0.03	0.33
70–80	M	3	−0.59	0.00	0.05	0.10	−0.01	0.69
70–80	W	1	−0.41	0.00	0.08	0.01	−0.07	0.09
70–80	W	2	−0.64	0.00	−0.03	0.22	0.04	0.29
70–80	W	3	−0.58	0.00	−0.03	0.25	0.02	0.51

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Table AII. *Continued*

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
>80	M	1	−0.49	0.00	−0.01	0.84	−0.06	0.54
>80	M	2	−0.67	0.00	−0.14	0.02	0.06	0.47
>80	M	3	−0.67	0.00	−0.01	0.89	−0.02	0.78
>80	W	1	−0.59	0.00	−0.05	0.59	0.07	0.47
>80	W	2	−0.56	0.00	−0.07	0.32	0.08	0.38
>80	W	3	−0.53	0.00	−0.05	0.18	−0.02	0.72
1998					−0.07	0.41	0.17	0.10
1999			−1.29	0.02	−0.08	0.26	0.08	0.42
2000			−1.68	0.00	−0.03	0.64	−0.01	0.92
2001			−1.75	0.00	−0.04	0.58	−0.17	0.08
2002			−1.75	0.00	0.06	0.37	−0.15	0.12
2003			−1.92	0.00	0.12	0.08	−0.19	0.04
2004			−1.92	0.00	0.21	0.00	−0.30	0.00
2005			−1.55	0.08	0.03	0.87	−0.23	0.27
LS			0.27	0.00	−0.05	0.09	−0.02	0.57
HS			0.21	0.00	−0.06	0.05	0.00	0.95
H			0.47	0.00	−0.14	0.00	−0.19	0.00
c			7.67	0.00	−2.23	0.00	8.69	0.00
No. of observations				72 433		65 129		11 192
d.f.				58		59		59
Pseudo R^2				0.246		0.034		
Log-likelihood				−6060		−28 876		−108 069
AIC				12 236		57 870		216 256
BIC				12 770		58 406		216 688
LR constant vs linear				χ^2_{24} (1462)		χ^2_{24} (67)		χ^2_{24} (68)
LR linear vs quadratic				χ^2_{24} (132)		χ^2_{24} (43)		χ^2_{24} (29)

Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period k. Part 3: Gamma model for the costs of hospital use in period k conditional on going to the hospital in period k. Health: 1 no difficulty, 2 at least one minor and no major difficulty, 3 at leastone major difficulty. Likelihood Ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence.

Table AIII. Regression results of the three-part model for ADL limitations, coefficients and p-values

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
t-independent								
50–60	M	2	−0.44	0.00	0.57	0.00	0.34	0.05
50–60	M	3	−0.44	0.00	1.07	0.00	0.26	0.27
50–60	W	1	−0.26	0.10	−0.17	0.03	−0.33	0.00
50–60	W	2	−0.50	0.00	0.30	0.01	−0.20	0.25
50–60	W	3	−0.19	0.48	1.09	0.00	0.72	0.00
60–70	M	1	−0.20	0.13	0.29	0.00	0.20	0.04
60–70	M	2	−0.48	0.00	0.93	0.00	0.48	0.00
60–70	M	3	−0.49	0.00	1.52	0.00	0.53	0.00
60–70	W	1	−0.55	0.00	0.11	0.14	−0.07	0.51
60–70	W	2	−0.53	0.00	0.55	0.00	0.08	0.54
60–70	W	3	−0.44	0.00	1.07	0.00	0.42	0.00
70–80	M	1	−0.38	0.00	0.80	0.00	0.20	0.04
70–80	M	2	−0.51	0.00	1.15	0.00	0.32	0.01
70–80	M	3	−0.53	0.00	1.67	0.00	0.75	0.00
70–80	W	1	−0.61	0.00	0.53	0.00	0.16	0.14
70–80	W	2	−0.52	0.00	1.03	0.00	0.41	0.00
70–80	W	3	−0.52	0.00	1.26	0.00	0.43	0.00
>80	M	1	−0.52	0.00	0.92	0.00	0.18	0.29

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Table AIII. *Continued*

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
>80	M	2	−0.50	0.00	1.35	0.00	0.41	0.02
>80	M	3	−0.59	0.00	1.48	0.00	0.71	0.00
>80	W	1	−0.84	0.00	0.73	0.00	0.18	0.29
>80	W	2	−0.62	0.00	0.88	0.00	0.38	0.02
>80	W	3	−0.47	0.00	1.23	0.00	0.53	0.00
t-dependent								
50–60	M	1	−0.60	0.00	0.03	0.10	0.00	0.99
50–60	M	2	−0.43	0.46	−0.01	0.78	−0.09	0.09
50–60	M	3	−1.70	0.01	0.04	0.53	0.12	0.11
50–60	W	1	1.25	0.02	0.03	0.09	0.08	0.00
50–60	W	2	0.81	0.46	0.05	0.14	0.02	0.75
50–60	W	3	−1.41	0.02	−0.02	0.70	−0.15	0.01
60–70	M	1	−0.52	0.09	0.06	0.00	0.03	0.13
60–70	M	2	−1.37	0.00	0.02	0.46	−0.02	0.53
60–70	M	3	−1.70	0.00	−0.02	0.58	0.02	0.59
60–70	W	1	0.56	0.14	0.05	0.00	0.02	0.30
60–70	W	2	−0.30	0.51	0.07	0.01	0.05	0.10
60–70	W	3	−1.39	0.00	0.03	0.36	0.03	0.39
70–80	M	1	−1.46	0.00	0.05	0.01	0.04	0.09
70–80	M	2	−2.05	0.00	0.06	0.07	0.04	0.31
70–80	M	3	−2.55	0.00	0.05	0.22	−0.07	0.09
70–80	W	1	−0.61	0.07	0.05	0.01	0.01	0.57
70–80	W	2	−0.95	0.01	−0.04	0.07	−0.05	0.11
70–80	W	3	−1.62	0.00	−0.04	0.10	0.00	0.93
>80	M	1	−2.15	0.00	−0.01	0.79	0.02	0.71
>80	M	2	−2.22	0.00	−0.05	0.32	0.04	0.58
>80	M	3	−2.26	0.00	−0.05	0.49	0.02	0.83
>80	W	1	−1.17	0.01	−0.03	0.54	0.04	0.51
>80	W	2	−1.79	0.00	−0.01	0.76	0.03	0.61
>80	W	3	−2.23	0.00	−0.11	0.00	0.00	0.93
1998					−0.07	0.38	0.14	0.14
1999			−0.93	0.02	−0.12	0.09	0.09	0.36
2000			−1.40	0.00	−0.05	0.43	0.01	0.91
2001			−1.44	0.00	−0.04	0.50	−0.12	0.19
2002			−1.53	0.00	0.05	0.45	−0.14	0.09
2003			−1.71	0.00	0.09	0.16	−0.16	0.07
2004			−1.76	0.00	0.18	0.01	−0.27	0.00
2005			−0.99	0.21	0.04	0.81	−0.31	0.12
LS			0.27	0.00	0.01	0.80	−0.07	0.04
HS			0.16	0.01	−0.02	0.52	0.00	0.95
H			0.41	0.00	−0.08	0.01	−0.20	0.00
c			7.38	0.00	−2.06	0.00	8.68	0.00
No. of observations			74 871		67 459		12 884	
d.f.			58		59		59	
Pseudo R^2			0.255		0.035			
Log-likelihood			−8161		−31 753		−125 602	
AIC			16 438		63 624		251 324	
BIC			16 973		64 162		251 959	
LR constant v.s. linear			χ^2_{24} (2028)		χ^2_{24} (80)		χ^2_{24} (84)	
LR linear v.s. quadratic			χ^2_{24} (173)		χ^2_{24} (26)		χ^2_{24} (32)	

Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period k. Part 3: Gamma model for the costs of hospital use in period k conditional on going to the hospital in period k. Health: 1 no difficulty, 2 at least one minor and no major difficulty, 3 at least one major difficulty. Likelihood Ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence.

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Table AIV. Regression results of the three-part model for comorbidity, coefficients and p-values

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
t-independent								
50–60	M	2	−0.32	0.47	0.45	0.00	−0.06	0.64
50–60	M	3	−0.52	0.31	0.72	0.00	−0.01	0.93
50–60	W	1	1.18	0.04	−0.14	0.12	−0.34	0.01
50–60	W	2	1.57	0.04	0.29	0.00	−0.27	0.04
50–60	W	3	0.44	0.47	0.59	0.00	−0.22	0.09
60–70	M	1	−0.69	0.07	0.43	0.00	0.22	0.07
60–70	M	2	−0.59	0.15	0.68	0.00	0.27	0.03
60–70	M	3	−1.67	0.00	1.24	0.00	0.29	0.02
60–70	W	1	−0.11	0.82	0.15	0.11	−0.13	0.34
60–70	W	2	0.65	0.27	0.41	0.00	−0.02	0.87
60–70	W	3	−0.08	0.86	0.91	0.00	−0.03	0.81
70–80	M	1	−1.30	0.00	0.87	0.00	0.11	0.43
70–80	M	2	−1.71	0.00	1.16	0.00	0.46	0.00
70–80	M	3	−2.15	0.00	1.57	0.00	0.22	0.10
70–80	W	1	−0.64	0.17	0.44	0.00	0.27	0.09
70–80	W	2	−1.09	0.01	1.01	0.00	0.16	0.26
70–80	W	3	−0.48	0.25	1.25	0.00	0.27	0.03
>80	M	1	−1.29	0.02	1.23	0.00	0.35	0.10
>80	M	2	−2.28	0.00	1.71	0.00	0.52	0.01
>80	M	3	−2.40	0.00	1.70	0.00	0.64	0.01
>80	W	1	−1.11	0.06	0.96	0.00	0.29	0.23
>80	W	2	−2.32	0.00	1.16	0.00	0.50	0.01
>80	W	3	−1.92	0.00	1.33	0.00	0.47	0.01
t-dependent								
50–60	M	1	−0.37	0.00	0.02	0.44	−0.05	0.09
50–60	M	2	−0.41	0.00	−0.01	0.79	0.03	0.29
50–60	M	3	−0.40	0.00	−0.02	0.45	0.08	0.06
50–60	W	1	−0.51	0.00	0.02	0.37	0.03	0.27
50–60	W	2	−0.57	0.00	0.01	0.61	0.04	0.24
50–60	W	3	−0.41	0.00	0.03	0.15	0.01	0.86
60–70	M	1	−0.46	0.00	0.04	0.07	0.01	0.74
60–70	M	2	−0.58	0.00	0.05	0.02	0.01	0.63
60–70	M	3	−0.36	0.00	0.01	0.60	0.02	0.61
60–70	W	1	−0.46	0.00	0.02	0.32	0.02	0.61
60–70	W	2	−0.59	0.00	0.05	0.03	0.01	0.77
60–70	W	3	−0.56	0.00	0.08	0.00	0.06	0.03
70–80	M	1	−0.53	0.00	0.03	0.31	0.05	0.16
70–80	M	2	−0.54	0.00	0.08	0.00	−0.01	0.77
70–80	M	3	−−0.59	0.00	0.05	0.12	0.07	0.07
70–80	W	1	−0.52	0.00	0.07	0.02	−0.01	0.77
70–80	W	2	−0.44	0.00	−0.03	0.31	0.01	0.75
70–80	W	3	−0.68	0.00	0.00	1.00	0.00	0.99
>80	M	1	−0.64	0.00	−0.04	0.51	−0.05	0.49
>80	M	2	−0.59	0.00	−0.04	0.52	−0.04	0.56
>80	M	3	−0.79	0.00	−0.06	0.46	−0.06	0.60
>80	W	1	−0.61	0.00	−0.03	0.55	0.04	0.57
>80	W	2	−0.55	0.00	−0.07	0.26	−0.04	0.55
>80	W	3	−0.55	0.00	−0.04	0.42	0.03	0.68
1998					−0.09	0.29	0.16	0.15
1999			−0.93	0.06	−0.09	0.22	0.09	0.37
2000			−1.41	0.00	−0.04	0.61	−0.01	0.95
2001			−1.53	0.00	−0.05	0.52	−0.13	0.19
2002			−1.49	0.00	0.03	0.63	−0.16	0.09
2003			−1.67	0.00	0.10	0.18	−0.19	0.05
2004			−1.68	0.00	0.19	0.01	−0.27	0.01
2005			−1.24	0.14	0.02	0.92	−0.24	0.25
LS			0.33	0.00	−0.06	0.03	−0.05	0.20

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Table AIV. *Continued*

			Part 1		Part 2		Part 3	
Age	Sex	Health	Coef.	p	Coef.	p	Coef.	p
HS			0.31	0.00	−0.09	0.00	−0.04	0.36
H			0.55	0.00	−0.20	0.00	−0.24	0.00
c			7.41	0.00	−2.21	0.00	8.73	0.00
No. of observations				70 262		63 175		10 737
d.f.				58		59		59
Pseudo R^2				0.245		0.039		
Log-likelihood				−5804		−27 675		−103 748
AIC				11 725		55 468		207 614
BIC				12 256		56 002		208 043
LR constant vs linear				χ^2_{24} (1445)		χ^2_{24} (52)		χ^2_{24} (53)
LR linear vs quadratic				χ^2_{24} (132)		χ^2_{24} (27)		χ^2_{24} (25)

Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period κ. Part 3: Gammamodel for the costs of hospital use in period κconditional on going to the hospital in period κ. Health: 1 no chronic disease, 2 at least one chronic disease, 3 more than one chronic disease. Likelihood ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence.

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