Population Ageing and Health Care
Expenditures: the Role of Life Expectancy

by

Friedrich Breyer, University of Konstanz and DIW Berlin
Normann Lorenz, University of Trier
Thomas Niebel, Centre for European Economic Research (ZEW), Mannheim

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Corresponding Author: Prof. Dr. Friedrich Breyer, Fachbereich Wirtschaftswissenschaften, Universität Konstanz, Fach D 135, D-78457 Konstanz, Phone (+49-7531) 88-2568, Fax -4135, email: friedrich.breyer@uni-konstanz.de

Abstract

It is still an open question whether population ageing as such is causing higher health care expenditures (HCE). According to the „red-herring“-hypothesis, the positive correlation between age and HCE is exclusively due to the fact that mortality rises with age and a large share of HCE is caused by proximity to death. As a consequence, rising longevity – through falling mortality rates – may even dampen the increase in HCE. However, a weakness of previous empirical studies is that they use cross-sectional evidence to make inferences on a development over time. In this paper we try to isolate the impact of rising longevity on the trend of HCE over time by using data for a pseudo-panel of German sickness fund members over the period 1997-2008. In a fixed-effects regression using the Intrinsic Estimator due to Yang et al. (2008), we find that age, mortality rate and life expectancy have a positive impact on per-capita HCE. A simulation on the basis of an official population forecast for Germany shows that real per-capita HCE will rise between 76 and 200 per cent until 2060.
1 Introduction

The ageing of population in most OECD countries will place an enormous burden on taxpayers over the next decades. Given this demographic change, previous fiscal policies in several of these countries were unsustainable, and major reforms of social insurance systems have been enacted, in particular with respect to public pension and long-term care financing systems. What is, however, not so clear is whether population ageing also jeopardizes the sustainability of social health insurance (see, e.g. Hagist and Kotlikoff 2005, Hagist et al. 2005). While there is no doubt that the revenue side of these systems will suffer from the shrinking size of future taxpayer generations, it is not so clear if rising longevity will place an extra burden on the expenditure side. If so, additional reforms of these systems would be necessary to guarantee the sustainability of these systems such as introducing more funding or limiting the generosity of benefits.

The impact of population ageing on health care expenditures (henceforth: HCE) has been heavily debated over the last decade. That a positive association of age and health expenditures in cross-sections is primarily due to the high cost of dying and rising mortality rates with age, was first observed by Fuchs (1984). Subsequently, Zweifel et al. (1999) have coined the term „red herring“ to characterize the erroneous conclusion from the cross-section correlation that population ageing due to increasing longevity implies rising HCE over time. As counter-evidence they showed that – when controlling for proximity to death – calendar age is not even a significant predictor of individual health care costs.

While this early study suffered from the weakness that it concentrated on patients in their last years of life, subsequent studies by several authors such as Stearns and Norton (2004), Shamani and Gray (2004), Zweifel et al. (2004) and Werblow et al. (2007) confirmed the red-herring hypothesis by demonstrating that even for persons who survived for at least four more years, there is hardly any age gradient in HCE, whereas the costs of the last year of life tends to decrease with the age at death (Lubitz et al. 1995). The latter finding is explained by the tendency of physicians to treat patients who have lived beyond a “normal life-span” less aggressively than younger patients with the same diagnosis and the same survival chances. An alternative explanation is the “compression-of-morbidity“ hypothesis postulated by Fries (1980), which states that with rising life expectancy the period of severe sickness becomes shorter and therefore annual HCE per capita may even fall as longevity increases. In this vein, Miller (2001) shows by simulation that, based on a negative relationship between age-at-death and death-related costs, an increase in longevity will dampen the growth of HCE.

However, an important weakness of almost all studies in the related literature is their reliance on cross-section expenditure data. Therefore, in drawing inferences from these studies for the development of HCE over time, proponents of the “red-herring” hypothesis commit the same error of which they accuse their opponents (i.e. those who believe that ageing increases health spending because per-capita expenditures increase with age). In particular, they overlook the fact
that increasing longevity not only means that 30 years from now average age at death will be higher but also that people at a certain age (say, 75) will on average have more years to live than present 75-year olds. As a consequence, future physicians will look at 75-year old patients with different eyes than present physicians do because the notion of a „normal life-span“ will have shifted upwards. This effect is consistent with the ethical justification of age-based rationing of health care services (Callahan 1987, Daniels 1985) and with the corresponding empirical literature which shows that some physicians indeed use age as a prioritization criterion in allocating scarce health care resources (for an overview see Strech et al. 2008).

Therefore, it is desirable to study how rising life expectancy has affected health care expenditures over time, which clearly requires both a time-series analysis and the explicit inclusion of an indicator of life expectancy. To our knowledge, there have been only two previous studies which have used life expectancy as an explanatory variable in a regression equation for HCE, viz. Shang and Goldman (2008) and Zweifel et al. (2005).

The former authors used a rotating panel of more than 80,000 Medicare beneficiaries and predicted for each individual his life expectancy, based on age, gender, race, education and health status and then performed a nonlinear-least-squares estimation of individual HCE. In this equation, predicted life expectancy turned out to be highly significant and negative, whereas age became insignificant when this variable was included. The interpretation of this result is, however, very similar to other studies in the red-herring literature because predicted life expectancy, if the value is low (say, a few years) is a proxy for time-to-death.

The latter authors, in contrast, used a panel of 17 OECD countries over a period of 30 years (1970-2000) as observations and tried to jointly explain HCE and life expectancy. As one of the determinants of HCE, they constructed an artificial variable “SISYPH” (for Sisyphus effect) by multiplying “life expectancy at 60” (averaged over gender) with the share of persons over 65 in the total population. The predicted value of this variable turned out to be a significantly positive predictor of HCE. The only problem with this result is that it does not allow disentangling the effects of the old age dependency ratio and life expectancy itself.

In this paper we make a new attempt at estimating the effect of rising life expectancy on HCE by using a pseudo panel of sickness fund members in Germany for a time span of 12 years (1997-2008). The data set, which was originally collected for calculating age and gender specific (average) HCE for purposes of risk adjustment, will be merged with data on age and sex specific (remaining) life expectancy published annually by the Max Planck Institute for Demography at Rostock. We then use the estimated relationship between age, life expectancy and HCE to simulate the future development of HCE as life expectancy increases according to official estimates.

The remainder of this paper is organized as follows. In Section 2 we describe the data, in Section 3 we state the theoretical hypotheses to be tested, in Section 4 we explain the methodol-
ogy of estimating the determinants of HCE, in Section 5 we present the regression results, in Section 6 we perform a simulation of the future development of HCE, and Section 7 concludes.

2 Data

The data used for this study were collected from three different sources. Data on HCE are published annually since 1997 by the German Federal (Social) Insurance Office (Bundesversicherungsamt (2008)). They are collected for purposes of calculating the risk adjustment payments between statutory sickness funds. Expenditure data comprise eight major expenditure categories including inpatient care, ambulatory care, dental care and pharmaceuticals. All expenditure data except those for dental care are based on a census of all sickness fund members and are separately calculated for demographic groups defined by age (in full years), sex, region (East vs. West Germany) and disability status, however, all persons older than 90 are classified into age 90.

The data set also contains the number of insured in each group (e.g. number of 20-year-old non-disabled males in West Germany). A peculiarity of this data set is that all disabled persons under the age of 35 are classified into age 35, so the number of disabled is zero below age 35 and too high for age 35. We used a data set provided by the German Statutory Pension Scheme (Deutsche Rentenversicherung 2009), whose definition of the term ‘disabled’ is almost identical to the one of the German Federal (Social) Insurance Office, to determine the relative share of each age bracket among all disabled up to age 35. We applied these weights to the number of insured being disabled and classified into age 35 to determine the number of insured being disabled for each age bracket up to 35.

Data on age and gender specific mortality rates and remaining life expectancy were taken from the Human Mortality Database (2008). These data apply to the German population as a whole and not only to sickness fund members. Since the omitted group, the privately insured, have on average higher incomes and life expectancy is positively associated with income in Germany (von Gaudecker and Scholz 2007, Breyer and Hupfeld 2009), the true life expectancy of sickness fund members is slightly exaggerated. On the other hand, this error should be small given that sickness fund members account for about 90 per cent of the German population.

The data on HCE are available for the period 1997 to 2008, and the same is true of mortality data. As there are 91 age groups for men and women separately, the total number of observations is 1820. Table 1 contains descriptive statistics on the data set. The following variables will be used in the regression equation:

- \( h_{a,t} \) (dependent variable), the average value of daily health care expenditures of all insured persons of age \( a \) in year \( t \), converted to Euros of 2008 by using the consumer price index;

- a set of dummy variables for age \( a \) for \( a=0,...,90 \);
- a set of dummy variables for the cohort (the year in which the person was born);

- $m_{a,t}$, the mortality rate, i.e. the share of persons of age $a$ in year $t$ who die within the period.

- $e_{a,t}$, the remaining life expectancy of members of age $a$ in year $t$,

- a set of dummy variables for year $t$ for $t=1997,\ldots,2008$.

### Table 1: Descriptive Statistics of the Data Set

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily health care expenditures</td>
<td>6.222</td>
<td>4.357</td>
<td>1.496</td>
<td>16.723</td>
</tr>
<tr>
<td>Age</td>
<td>45</td>
<td>26.274</td>
<td>0</td>
<td>90</td>
</tr>
<tr>
<td>Mortality rate</td>
<td>0.0222</td>
<td>0.0464</td>
<td>0.00005</td>
<td>0.2986</td>
</tr>
<tr>
<td>Remaining life expectancy</td>
<td>37.01</td>
<td>23.126</td>
<td>2.89</td>
<td>82.42</td>
</tr>
</tbody>
</table>

### 3 Testable Hypotheses

The main focus of the paper will be the effect of „population ageing”, measured by an increase of life expectancy, on average HCE of a population group. However, a complete model of the determination of HCE must include all variables mentioned in the previous section. The following theoretical predictions are derived from the literature and will be tested in the empirical estimation:

**Age**: According to more “traditional” theory, HCE will be decreasing with age in the age range 0-20, approximately constant between 20 and 60 and increasing with age for age above 60. In contrast, the red-herring hypothesis states that HCE will be independent of age for age above 20.

**Mortality**: HCE will be increasing in the mortality rate of the population group.

**Life expectancy**: HCE will be increasing in the remaining life expectancy (RLE) as physicians will spend more resources on patients who have “more to gain” from an intervention. The relationship between RLE and HCE should, however, be concave since this effect should play no role for values of RLE beyond some threshold. Alternatively, RLE should be important only above a certain age.

**Time**: HCE will be increasing over time due to medical progress.
4 Estimation Strategy

The data set is a „pseudo panel” in the sense of Deaton (1985). Verbeek and Nijman (1992) have shown that for a sufficiently large number of individuals in each group, the group averages are unbiased estimators of the “true” value in the population.

We use the dependent variable “health care expenditures” in logarithmic form so that, when we enter time (i.e. calendar year) as a regressor, we implicitly estimate a model with exponential (rather than linear) growth of the expenditure variable.

Following Deaton (1997), this variable can be subject to age and cohort effects in addition to the time effect, so that a full specification would require writing

\[
\ln h_{a,t} = \beta_0 + g(\text{age}, \text{cohort}, \text{year}) + u_{a,t},
\]

where \( u_{a,t} \) denotes the error term. However, this specification suffers from the well known problem of perfect multicollinearity since

\[
\text{age} = \text{year} - \text{cohort}.
\]

There are two ways to deal with this problem. The first one is to simply ignore one of the three variables age, year or cohort. Because our data set is a pseudo panel where the “individuals” are cohorts, this variable cannot be dropped in the analysis. Obviously, neither the age effect nor the year effect (medical progress) can be dropped, either.

The second one is to impose some exogenous restrictions on parameters so that the three effects can be disentangled.\(^1\) In the following we concentrate on the case that the age, year and cohort effects are captured by three sets of dummy variables, so that equation (1) becomes:

\[
\ln h_{a,t} = \beta_0 + \sum_a \beta_{1a} \text{age}_a + \sum_c \beta_{2c} \text{cohort}_c + \sum_t \beta_{3t} \text{year}_t + u_{a,t}
\]

For a data set comprising \( A \) age-classes and \( T \) years, the full sets of dummies would consist of \( A \) age-dummies, \( T \) year-dummies and \( A+T-1 \) cohort dummies. With an intercept included, for any set of dummy variables partitioning the data set, one dummy variable has to be dropped, so that the number of dummy variables in (3) effectively is \((A-1) + (T-1) + (A+T-2) = 2A+2T-4\). However, because of (2), these \( 2A+2T-4 \) dummy variables are perfectly collinear, so that the coefficients cannot be estimated.

The usual way to solve this problem is to impose the restriction that two (usually but not necessarily adjacent) coefficients are equal: e.g. \( \beta_{3,T-1} = \beta_{3,T} \) if it is assumed that there is no time effect going from \( T-1 \) to \( T \), or \( \beta_{1,20} = \beta_{1,21} \) if it is assumed that 20 and 21-year-olds have

\(^1\) Of course, dropping one of the variables means imposing the restriction that all coefficients on this variable are zero. However, since this is usually not made explicit, we mention it as a separate way to deal
equal health care expenditures. If one can be confident that this assumption is correct, this will correctly disentangle the age period and cohort effect. As shown by Yang et al. (2008), the resulting estimates can be seriously misleading, if this assumption is not warranted. They propose a new estimator, which they called “Intrinsic Estimator”.

The idea of the Intrinsic Estimator is the following: If (3) is written in matrix notation as $y = X\beta + u$, then with perfect multicollinearity, $X$ does not have full rank, so that $\hat{\beta} = (X'X)^{-1}X'y$ cannot be computed since $X'X$ is singular. An infinite number of different vectors $\hat{\beta}$ equally minimizes the sum of squared residuals. The Intrinsic Estimator then chooses the one $\hat{\beta}$ that does not depend on the dimension of the matrix $X$, i.e. that is independent of $A$ and $T$; and this is done by projecting any $\hat{\beta}$ onto the non-null subspace of the matrix $X$. In a Monte Carlo Study they show that the Intrinsic Estimator is superior to assuming that two of the dummy variables are equal, even if the true difference between the two dummy variables is small.

In line with the theoretical predictions above, we use “remaining life expectancy” in two alternative versions: a) in logarithmic form, b) interacted with a dummy variable for age in years. The coefficients of the latter variables can be interpreted in the following way: if life expectancy at age $x$ increases by one year, then HCE increase by a certain percentage. We also include the share of persons who died in the respective period as a regressor to capture the effect of mortality on HCE.

The data set contains separate HCE values for men and women, and for East and West Germany. As the results will be used for a simulation of future HCE and population forecasts exist depending on sex but not on region, we aggregate HCE with respect to region. As the data set is a pseudo panel and the respective cohort-age cells contain different numbers of observations, the results from the simple fixed-effects panel estimation may not be efficient. Therefore, the data for each cohort are weighted by the inverse of the number of observations in the respective cells.

Moreover, the highest age group for which data are available is the group “90+”, which differs from all other age groups, which are one-year age groups. We drop this group from our analysis for two reasons: first, this group is heterogeneous because it contains more than ten different age groups; and secondly population mortality rates are not very representative for the persons enrolled in Social Health Insurance because the privately insured have a higher life expectancy and therefore their share is particularly high at very high ages.

with the problem of perfect multicollinearity.
5 Regression Results

In Table 2 we present the results for log HCE as the dependent variable. The table contains the results of the weighted intrinsic estimator, separately for men and women, where we use robust standard errors. Columns 1 and 5 refer to regressions on age dummies and time trend only, in columns 2 and 6, the mortality rate is added, and columns 3 and 7 contain the full model, including the log of remaining life expectancy. Columns 4 and 8 contain alternative estimations in which only the RLE of older persons is included. This is achieved by interacting RLE with dummies for the six oldest 5-year age brackets, starting at age 60. The estimations in columns 1, 2, 5 and 6 are needed to compare different simulation versions only and are therefore not commented here. In the following we concentrate on the estimations in columns 3 and 4 (for men) and 7 and 8 (for women).

Each of these estimations contains a set of 89 age dummies plus 101 cohort dummies the coefficients of which are not printed in the tables. Instead, Figures 1 through 3 (in the Appendix) present the patterns of these coefficients graphically. We observe that the age dummies show a familiar picture: a high value for newborns, then a decline up to age 3, followed by a relatively flat portion up to age 45 (with somewhat higher expenditures for women in child-bearing age), and then a steep rise until age 85 with a flat portion thereafter.²

The coefficients of the cohort dummies are monotonically declining except for the last ten cohorts which we observe only in childhood. The general pattern confirms the well-known fact that more recent cohorts are healthier at any given age and therefore need less medical care than older cohorts.

The coefficients of the year dummies have to be interpreted as deviations from mean expenditures. The coefficients generally show a clear and highly significant increasing trend in per-capita health expenditures both for men and for women. An exception occurs for women when life expectancy is interacted with age groups (column 8). Here the time trend almost completely vanishes. Moreover, the time trend is not monotonic, but there is a noticeable downward blip in the year 2004, in which a major health care reform took effect in Germany. The estimated slope of the time trend for men is remarkably stable and suggests an annual increase of HCE on the order of 2 per cent, and the same is true for women in the equation with log RLE

² The increase at age 89 does not have to be taken too seriously, because the highest age groups have fewer members and therefore standard errors tend to rise considerably above age 85.
Table 2: Regression Results, weighted intrinsic estimator, dep. variable: log of daily HCE

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<td>Log RLE</td>
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<td>.180</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.949</td>
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<td>-</td>
<td>-</td>
<td>.016</td>
<td>(.002)</td>
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<td>.069</td>
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<td>.088</td>
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<td>-</td>
<td>-.115</td>
<td>(.028)</td>
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<td>-.049</td>
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<td>-.038</td>
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<td>(.043)</td>
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<tr>
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<td>.012</td>
<td>(.000)</td>
<td>.012</td>
<td>(.000)</td>
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<td>(.000)</td>
<td>.030</td>
<td>(.000)</td>
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<td>(.000)</td>
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<td>(.000)</td>
<td>-.011</td>
<td>(.000)</td>
<td>-.010</td>
<td>(.000)</td>
<td>-.010</td>
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<tr>
<td>Year 2005</td>
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<td>.062</td>
<td>(.000)</td>
<td>.036</td>
<td>(.000)</td>
<td>.039</td>
<td>(.000)</td>
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<tr>
<td>Year 2007</td>
<td>.064</td>
<td>(.000)</td>
<td>.088</td>
<td>(.000)</td>
<td>.063</td>
<td>(.000)</td>
<td>.067</td>
<td>(.000)</td>
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<tr>
<td>Year 2008</td>
<td>.091</td>
<td>(.000)</td>
<td>.137</td>
<td>(.000)</td>
<td>.089</td>
<td>(.000)</td>
<td>.094</td>
<td>(.000)</td>
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<tr>
<td>Constant</td>
<td>1.549</td>
<td>(.000)</td>
<td>1.423</td>
<td>(.000)</td>
<td>.825</td>
<td>(.505)</td>
<td>-1.484</td>
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<tr>
<td>Age and co-</td>
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<td>included</td>
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<td>included</td>
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<tr>
<td>hort dummies</td>
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</tbody>
</table>

p-values in parentheses, **bold figures** = significant at $\alpha = .05$. 

9
The coefficients of mortality are all positive and significant at the 5 per cent level. The coefficients suggest that expenditures for persons in their last year of life are about 4 to 8 times as high as for the average sickness fund member. These estimates are roughly in line with findings from previous studies. E.g., Lubitz and Riley (1993) found that the 5 per cent decedents account for 25-30 per cent of total Medicare expenditures. The Lubitz-Riley results imply that decedents spend about 6 times as much as survivors.

The log of remaining life expectancy turns out to be highly significant and positive for women, but insignificant for men. When the interaction effects of RLE with 5-year age groups are entered, the results again differ between genders: for men, only in the age group 60-64 there is a significant positive effect of RLE on HCE, whereas in the highest age group (85-89 years), the effect is reversed. For women, in all age groups except the highest one, an increase in RLE significantly raises health care expenditures.

We conclude that the hypotheses stated in Section 3 are on the whole supported by the results; in particular the mortality rate has a significant positive effect on HCE, and the same is true for remaining life expectancy of women. This implies that the sign of the total effect of population ageing, which leads both to a decline in mortality and an increase in life expectancy, is unclear. Therefore, we have to use simulation methods to determine whether the total effect will be positive, given the demographic development predicted for Germany.

6 Simulation Results

Forecasts on the size and composition of the population in Germany over the following decades are published every three years by the German Statistical Office. The most recent forecast is the “12. koordinierte Bevölkerungsvorausberechnung” (Statistisches Bundesamt 2009). In addition, the Office provided us estimates of the development of age-specific mortality rates over the period until 2060. From these data, we could calculate the time paths of age-specific remaining life expectancy. However, the German Statistical Office uses two different forecasts of mortality, the “most likely one” (LE1) and one with an even stronger increase in longevity (LE2). In our simulations we shall use only the data from the LE1 model.

In the following we report the results of simulations reaching until the year 2060 on the basis of the three different sets of explanatory variables used in Table 2:

Model 1: age dummies and a time trend,
Model 2: age dummies, mortality and a time trend,
Model 3: age dummies, mortality, log life expectancy and a time trend,
Model 4: age dummies, mortality, life expectancy for 5-year age groups and a time trend.
The time trend is calculated by estimating a linear trend from the coefficients of the year dummies. Furthermore, the cohort effects are not taken into account because we have no way of knowing how future cohorts will behave relative to the cohorts included in the data. The results are calculated for men and women separately but reported in summary figures (see Table 3).

Table 3: Simulation Results for daily health care expenditures (2008 = 1.000)

<table>
<thead>
<tr>
<th>Model</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Age dummies, all</td>
<td>Age dummies, time, mortality</td>
<td>Age dummies, time, mortality, log RLE</td>
<td>Age dummies, time, mortality, RLE age groups</td>
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<td>1.17</td>
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The result in column 1 suggests that a “naïve” application of the present age profiles of HCE to a changed demographic composition would result in a doubling of real per-capita HCE between 2008 and 2050. However, the results differ between genders: while for women the total increase is only 60 per cent, for men it amounts to 140 per cent. Adding the mortality rate dampens this increase only very slightly to 54 per cent and 130 per cent, respectively so that the “red-herring” effect seems to be very small in these data.
Adding the life expectancy variables has a very distinct effect on the forecasted increase for the two genders: while for men this increase rises very slightly to either 137 or 142 per cent, depending upon the specification of the RLE variable, the result for women differs extremely between the specification: while with the age group specific RLE the increase over time almost vanishes (+ 25 per cent in 52 years), the opposite is true if the simulation is based on log RLE, where the increase steepens to 245 per cent in 52 years. The last row of Table 3 translates these findings into annual growth rates. For men, this increase is estimated at about 1.7 per cent, independent of the particular specification, whereas for women the estimate varies between .4 per cent and 2.4 per cent per year. Combining the two, the annual growth rate of health care expenditures is estimated at between 1.1 and 2.1 per cent. So our estimate of the pure demographic effect is positive but moderate.

The results are pretty much in line with findings from a previous study on the basis of individual expenditure data (Breyer and Felder 2006), in which a “naïve” forecast of per-capita HCE (with no distinction between survivors and decedents’ costs) resulted in a 23.9 per cent increase between 2002 and 2050, whereas adding this distinction – which is similar to adding the mortality rate in the present model – flattened the slope to 19.5 per cent. In addition, we argue here that the Breyer/Felder simulation failed to account for the positive effect of life expectancy changes on medical practice and thus on per-capita expenditures.

This increase is also similar in size to historical figures for real per-capita GDP growth rates. Thus one may conclude that if German society succeeds in keeping per-capita GDP growth roughly constant – despite an ageing and shrinking work-force –, then it will be able to finance even a rising health care budget without a drastic increase in contribution rates.

7 Conclusions and Caveats

In this paper we have use a pseudo-panel of HCE data for Germany to demonstrate that per-capita health care expenditures are significantly influenced by the age composition of the population, by mortality rates and by the development of longevity, as measured by the age-specific remaining life expectancies of the aged population. We interpret this effect as the reaction of the medical profession’s willingness to perform expensive treatments on elderly patients to what is commonly perceived as a “normal life span”.

The results of the simulations based on the regression coefficients show that if past trends continue, per-capita health care expenditures will rise by between 1.2 and 1.4 per cent per year. Moreover, while we can confirm that simulations on the basis of the population age structure alone are misleading, the same applies when only age-specific mortality rates are added. The effect of population ageing can not be ignored, either. One way to take it into account is to include a measure of age-specific life expectancy.
The type of data employed for this study has important advantages, but also certain drawbacks. To our knowledge, this is the first attempt to quantify the effect of rising longevity on the development of health care expenditures over time. However, since we had to use age and gender group averages instead of individual expenditure data, the well-known effect of time-to-death on HCE expenditures is accounted for only in a very indirect form: by estimating the impact of the mortality rate within a population group on average expenditures. Adding this variable to a set of regressors which already includes age and cohort effects and a time trend certainly raises problems of identification. Thus, it is desirable to collect individual expenditure data over time in order to be better able to disentangle the respective effects.

It can further be argued that mortality and life expectancy themselves are influenced by HCE and therefore endogenous. Thus we pursued an instrumental variable estimation as an alternative. However, both lagged HCE and lagged mortality proved to be weak instruments and coefficients of the second stage were beyond any reasonable values; in addition, second-stage estimations were not robust with respect to the regression procedure: coefficients of predicted mortality had a different sign when the panel estimation was replaced by OLS. Thus we infer that the single-equation estimates are more reliable because they are more robust with respect to changes in specification. Moreover, unlike in individual data, for group averages the causal effect of HCE on mortality should not be too strong. Any correlation of HCE and mortality over time is probably due to medical progress which both raises expenditures and lowers mortality. Our simulation exercise is not invalidated if the effect of mortality on HCE is not causal. We rather utilize the fact that demographic trends are better predictable than expenditures per se and rely on the assumption that the underlying trend in medical progress will persist.

We sum up by stating the main purpose of this paper, namely to examine whether ageing – i.e. an increase of life expectancy – as such will increase health expenditures, and the answer to this question is a clear “yes”.
References


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Fuchs, V.R (1984), Though much is taken: reflections on aging, health and medical care, Milbank Memorial Fund Quarterly/Health and Society 61, 143-166.


Human Mortality Database (2008) URL www.mortality.org. – University of California,Berkeley (USA), and Max Planck Institute for Demographic Research (Germany)


Appendix

Figure 1: Coefficients of age dummies and year dummies, dep. var. log HCE (men)\(^3\)

![Figure 1](image1.png)

Figure 2: Coefficients of age dummies and year dummies, dep. var. log HCE (women)

![Figure 2](image2.png)

Figure 3: Coefficients of cohort dummies, dependent variable log HCE, (left panel: men, right panel: women)

![Figure 3](image3.png)

\(^3\) Regressions with no other explanatory variables