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Abstract

It is still an open question whether increasing life expectancy 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 reduce 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 1997-2009. Using dynamic panel data models, we find that age, mortality rate and five-year survival rates have a positive impact on per-capita HCE. Our explanation for the last finding is that physicians treat patients more aggressively if they think the result will pay off for a longer time span, which we call "Eubie Blake effect". A simulation on the basis of an official population forecast for Germany is used to isolate the effect of demographic ageing on real per-capita HCE over the next decades.

JEL-**classification:** H51, J11, I19.

Keywords: health care expenditures, ageing, longevity, 5-year survival rate.

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If I'd known I was going to live this long,
I would have taken better care of myself.
(Eubie Blake on his alleged 100^{th} birthday)

1 Introduction

The ageing of population in most OECD countries will place an enormous burden on tax payers 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. However, what remains unclear is whether population ageing also jeopardizes the sustainability of social health insurance (see, e.g. Hagist and Kotlikoff (2005) and 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, Felder, and Meier (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), Seshamani and Gray (2004), Zweifel, Felder, and Werblow (2004) and Werblow, Felder, and Zweifel (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 tend to decrease with the age at death (Lubitz, Beebe, and Baker 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, 80) will on average have more years to live than present 80-year olds. We suggest that physicians, e.g. when implanting an artificial hip into a patient, will make a conjecture how long the patient will benefit from this treatment, and this depends upon his expected longevity. In that respect, the physician (and maybe the patient, too) will behave in a way described in the famous quotation by Eubie Blake. This effect will lead to

a similar physician behaviour as "age-based rationing" of health care services when the notion of a "normal life span" (Callahan (1987), Daniels (1985)) shifts over time with rising longevity. Indeed, the empirical literature shows that some physicians use age as a prioritization criterion in allocating scarce health care resources (for an overview see Strech, Synofzik, and Marckmann (2008)).

To test whether there is a "Eubie Blake effect", it is desirable to study how rising life expectancy has affected health care expenditures *over time*, which clearly requires a data set that comprises this variable, or an indicator of it, and covers several years.

To our knowledge, there have been only three previous studies which have used life expectancy as an explanatory variable in a regression equation for HCE, viz. Shang and Goldman (2008), Zweifel, Steinmann, and Eugster (2005) and Bech et al. (2011).

Shang and Goldman (2008) used a rotating panel of more than 80,000 Medicare beneficiaries and predicted for each individual his life expectancy, based on age, sex, 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.

Zweifel, Steinmann, and Eugster (2005), 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 both sexes) 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. A problem with this result is that it does not allow disentangling the effects of the old age dependency ratio and life expectancy itself.

Bech et al. (2011) consider per-capita HCE for a panel of 15 EU member states over the period 1980 to 2003 and find that both mortality and remaining life expectancy at age 65 have a significant positive effect on HCE in the following year. They then calculate long-run elasticities of HCE with respect to these variables and find a positive value only for life expectancy, so that a linear increase in life expectancy at 65 is associated with an exponential growth in per-capita HCE.

In this paper, we make a new attempt at estimating the effect of rising longevity on HCE by being the first to use a measure of longevity that is especially common among physicians: 5-year survival rates. In medical studies, in particular those concerned with specific diseases, this measure is used rather than life expectancy as such.

The data set we employ is a pseudo panel of sickness fund members in Germany, which was originally collected for calculating age and sex specific (average) HCE for purposes of risk adjustment. This data set, which covers the years 1997 to 2009, is merged with data on mortality rates published annually by the Max Planck Institute for Demographic Research at Rostock.

To determine the impact of longevity we estimate (dynamic) panal data models; to disentangle age, period and cohort effects, we apply the intrinsic estimator (Yang et al. (2008)). We then use the estimated relationship to show the effect of an increase in survival rates according to official statistics on average HCE.

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 methodology 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 in this study come from three different sources. Data on HCE are taken from the German Federal (Social) Insurance Office ("Bundesversicherungsamt", BVA).[1] They are collected for purposes of calculating the risk adjustment payments between statutory sickness funds. They comprise eight major expenditure categories including inpatient care, ambulatory care, dental care and pharmaceuticals, and are based on a census of all sickness fund members (except for dental care). The data set contains the variables age (in full years), sex, and year, and – for each age-sex group in each year – the average HCE and the number of individuals in this group.[2] All persons older than 90 are classified into the age-group 90 by the Federal (Social) Insurance Office.

Data on age and sex specific mortality rates, taken from the Human Mortality Database (2011), were used to calculate 5-year survival rates. 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 population-based survival rates constitute an upward-biased estimate for the true survival rates of sickness fund members. On the other hand, this error should be rather small given that sickness fund members account for about 90 per cent of the German population.

As mentioned before, in the data set provided by the German Federal (Social) Insurance Office the highest age group contains the average HCE of all individuals of age 90 and above. Since we have no information about the age distribution for this group, we could not compute their average mortality and survival rate. We therefore drop this group, which amounts to a loss of 0.71% person-days.[3]

Table 1: Descriptive Statistics of the Data Set

	Man				**Woman**			
	mean	std.dev.	min	max	mean	std.dev.	min	max
Age	44.5		0	89	44.5		0	89
Cohort	1958.5		1908	2009	1958.5		1908	2009
HCE	6.2437	4.7329	1.7812	17.6005	6.1312	3.8728	1.5020	15.7070
$MORT$	.0233	.0437	.00007	.2275	.0153	.0321	.00005	.1711
$SR5$	.8785	.2021	.1687	.9996	.9117	.1685	.2603	.9997

Our data set comprises the period 1997 to 2009. As there are 90 age groups (0 to 89) for men and women separately, the total number of observations is 2340. Table 1 contains descriptive statistics on the data set. Since we perform the estimations separately for men and women, we present these statistics separately, too. Table 2 shows that 5-year survival rates have been

[1] The official risk adjustment data, which the BVA publishes on its website, are smoothed. We use the unsmoothed data and thank Dirk Göpffarth for making this data set available to us.

[2] To be more precise, the variables are *average HCE per day* and *number of person-days*, i.e., the number of insured times the average number of days per year an individual of this age-sex group is insured. In addition, the data set contains these two variables also separately for the two regions east and west, however only until 2007. Since 2008 there is no distinction according to region in the risk adjustment scheme any more.

[3] Further reasons for dropping this group are: 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.

Table 2: 5-year survival rates: Level in 1997 (per cent) and increase from 1997 to 2009 (percentage points)

	Man		**Woman**	
	$SR5$		$SR5$	
Age	1997	Δ	1997	Δ
60	91.1	2.4	95.9	0.8
65	86.1	4.3	93.2	1.9
70	79.1	5.9	88.3	3.4
75	67.9	6.9	79.5	4.6
80	51.2	9.0	64.6	5.6
85	31.6	8.6	43.6	4.7
90	14.0	4.0	22.1	1.1

increasing by up to 9 percentage points for men; for women the increase is smaller but still up to 5.6 percentage points. These values refer to the population as a whole; for specific subgroups the increase can be higher, (e.g. for certain chronic conditions, survival rates may have increased more, so the way physicians treat patients with these particular conditions may have changed over time even more).

The following variables will be used in the regression equations:

- $HCE_{c,a,t}$ (dependent variable), the average value of daily health care expenditures of all insured persons in cohort c of age a in year t, converted to Euros of 2009 by using the consumer price index;
- a set of $A = 90$ dummy variables Age_a for each age a with $a = 0, \ldots, 89$;
- a set of dummy variables $Cohort_c$ for each cohort c with $c = 1908, \ldots, 2009$, (the year in which the person was born);
- a set of $T = 13$ dummy variables $Year_t$ for each year t with $t = 1997, \ldots, 2009$;
- $MORT_{c,a,t}$, the mortality rate, i.e. the share of persons in cohort c of age a in year t who die within that year;
- $SR5_{c,a,t}$, the 5-year survival rate of persons in cohort c of age a in year t.

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.

5-year survival rates: HCE will be increasing in 5-year survival rates ($SR5$) as physicians will spend more resources on patients who have "more to gain" from an intervention. This effect is especially important for older patients.[4]

Time: HCE will be increasing over time due to medical progress.

4 Estimation Strategy

As is well known, the age profile of HCE has a different shape for men and women; we therefore perform both the regression and the simulation separately for men and women.

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.

Following Deaton (1997), the dependent variable will not only depend upon the "health" variables mortality and 5-year survival rates, but can also be subject to age and cohort effects in addition to the time effect, so that a full specification would require writing

$$HCE_{c,a,t} = g(c,a,t) + \gamma_1 MORT_{c,a,t} + \gamma_2 SR5_{c,a,t} + u_{c,a,t}, \tag{1}$$

where $u_{c,a,t}$ denotes the error term and $g(\cdot)$ is some general function of cohort, age and year, including the constant term. However, this specification suffers from the well-known problem of perfect multicollinearity since age equals year minus cohort:

$$a = t - c. \tag{2}$$

In our case, since we suppose the relationship between age, time and HCE to be non-linear, we use dummy variables for the respective age groups, years and cohorts, i.e we want to estimate model (1) with

$$g(c,a,t) = \sum_c \beta_c Cohort_c + \sum_a \alpha_a Age_a + \sum_t \delta_t Year_t. \tag{3}$$

Of course, the problem of perfect multicollinearity applies to the dummy variables specificiation in (3) as well.[5] There are in principle three strategies to deal with this problem:

[4] Using the 5-year survival rate has an important advantage over the variable "life expectancy": In younger age groups life expectancy falls almost linearly with age, whereas survival rates vary very little with age and start falling only later. Here the variance with age and over time occurs almost exclusively in older age groups, and the effect of this on HCE is exactly what we want to test.

[5] For a data set comprising A age-classes and T years, the full sets of dummies consists 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.

1. to drop one of the variables age, cohort or time,
2. to impose restrictions on the coefficients of the dummy variables,[6]
3. to use the intrinsic estimator due to Yang et al. (2008).

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 usual way then to solve the multicollinearity problem is to impose the restriction that two (usually but not necessarily adjacent) coefficients are equal: E.g. if $\delta_{2000} = \delta_{2001}$, it is assumed that there is no time effect going from year 2000 to 2001; if $\alpha_{20} = \alpha_{21}$, then it is assumed that 20 and 21-year-olds have equal health care expenditures. If one can be confident that this assumption is valid, this will correctly disentangle the age, period and cohort effect.

However, as shown by Yang et al. (2008), the resulting estimates can be seriously misleading, if this assumption is not warranted.[7] They propose a new estimator, which they called "Intrinsic Estimator". This estimator chooses of all possible combinations $(\hat{\alpha}, \hat{\beta}, \hat{\delta})$, which minimize the sum of squared residuals, the one, that does not depend on the dimension of the matrix of explanatory variables, i.e., that is independent of A and T. 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 them is small.

However, it is important to bear in mind, that the Intrinsic Estimator and the fixed effects panel estimator (with any restriction) only differ in the coefficients for age, period and cohort, but not in the coefficients for the other variables. This means that the coefficients for the variables we are mainly interested in, i.e., $MORT$ and $SR5$, do not depend upon whether the intrinsic estimator is used or, if not, which particular restriction is imposed.

In the following, we shall first use the fixed-effects panel estimator (with an arbitrary restriction) to derive estimates of the coefficients of $MORT$ and $SR5$, i.e. we estimate the model

$$HCE_{c,a,t} = \gamma_1 MORT_{c,a,t} + \gamma_2 SR5_{c,a,t} + \sum_c \beta_c Cohort_c + \sum_a \alpha_a Age_a + \sum_t \delta_t Year_t + u_{c,a,t}. \tag{4}$$

There are two possible reasons why this model may be misspecified: First, the true relationship may be dynamic so that there is persistence in HCE. To account for this problem, we also estimate the following dynamic panel model:

$$\begin{aligned} HCE_{c,a,t} &= \phi HCE_{c,a-1,t-1} + \gamma_1 MORT_{c,a,t} + \gamma_2 SR5_{c,a,t} \\ &\quad + \sum_c \beta_c Cohort_c + \sum_a \alpha_a Age_a + \sum_t \delta_t Year_t + u_{c,a,t}. \end{aligned} \tag{5}$$

[6] 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 with the problem of perfect multicollinearity.

[7] In our estimation it turns out that when we apply the usual panel estimator and omit two adjacent age dummies, the sign of the time trend depends critically on which two age dummies are chosen. E.g. it is negative if the ages 6/7, 7/8, 13/14, 14/15, 15/16, 16/17 or 24/25 are omitted from the equation for men. This lack of robustness is a strong reason for discarding the panel estimator in favour of the Intrinsic Estimator to determine the coefficients for age, period and cohort.

Secondly, the variables may be non-stationary so that there may be the problem of spurious regression. For this reason we test for unit roots. Since these tests do not reject non-stationarity in the explanatory variables, (although they do for HCE), we also estimate the models (4) and (5) in first (and second) differences, i.e. we replace HCE, $MORT$ and $SR5$ by ΔHCE, $\Delta MORT$ and $\Delta SR5$. We estimate the dynamic panel model (4) by GMM, using both the difference-GMM-estimator by Arellano and Bond (1991) and the system-GMM-estimator by Blundell and Bond (1998).

For the following reason we do not use $SR5$ as such but its predicted values as explanatory variable. We argued that a physician will take the 5-year survival rate into account when deciding whether to perform an expensive or risky procedure or on which patients to ration (most). However, during the year t, the physician does not know the 5-year survival rate $SR5_{c,a,t}$, as this is a measure derived from the mortality rates in the same year, which are not known until the end of the year. It is therefore an informed guess of the survival rate the physician will have in mind. One possible proxy for this variable would be its value in the previous year (for the same age), $SR5_{c-1,a,t-1}$, but this is certainly not the best option: First, survival rates are increasing over time, so there would be a systematic downward bias in this proxy. Secondly, as the survival rate in a particular year $t-1$ is derived from the mortality rates in $t-1$, they may depend heavily upon singular events such as a flu epidemic. Thus it is not the best alternative to base the informed guess only on $SR5_{c-1,a,t-1}$, but on a few more values. We therefore use as a proxy the predicted value of $SR5_{c,a,t}$ from a regression of the $SR5$-values (of age a) in years $t-5$ to $t-1$ on a time trend.

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 and have to be weighted by the square root of the cohort size, see Deaton (1985). Because in our pseudo panel the cohort size is not constant over time, we could use different weights for each cohort-age cell. However, Inkmann, Klotz, and Pohlmeier (1998) show that estimation results can be unstable if the cohort size differs considerably and therefore propose to weight by the average weight for each cohort. We therefore use weights that do not differ in the time dimension.

5 Regression Results

5.1 Unit root tests

We first employ the unit root tests by Harris and Tzavalis (1999) and by Im, Pesaran, and Shin (2003) without and with different number of lags. Table 3 shows an overview of the results; the detailed results can be found in Tables 7 to 9 in the Appendix. For the dependent variable HCE, non-stationarity is clearly rejected. For $MORT$ and $SR5$, non-stationarity in levels is never rejected, as all p-values are very close to 1. For first differences, the results are ambiguous as the null hypothesis is only rejected for some of the tests. For second differences, the null is always rejected. Therefore, we not only present the results for the estimation in levels, but by way of a robustness check, in first and second differences as well.

5.2 Estimation results

In Table 4 we present the regression results. In column (1), results for the fixed effects model with only $MORT$ as an additional explanatory variable can be found. In column (2), $SR5$ is

Table 3: Unit root tests: Rejection of H_0: non-stationarity

	Men			**Women**		
	level	Δ	Δ^2	level	Δ	Δ^2
HCE	yes	yes	yes	yes	yes	yes
$MORT$	no	yes/no	yes	no	yes/no	yes
$SR5$	no	yes/no	yes	no	yes/no	yes

added. Columns (3) and (4) then show the results for the dynamic panel model with both $MORT$ and $SR5$, estimated by the difference-GMM-estimator due to Arellano and Bond (1991) and by the system-GMM-estimator due to Blundell and Bond (1998). In all the GMM-estimations, HCE_{t-1} and $SR5_t$ are regarded to be predetermined as they do not depend on the error term in period t. However, we allow for $MORT_t$ to be endogenous by using only lagged values as instruments. To limit instrument proliferation, the number of instruments was reduced using the *collapse*-option of STATA's *xtabond2*-command, see Roodman (2006).

These four models are estimated with the variables HCE, $MORT$ and $SR5$ in levels – see columns (1) to (4) – and in first differences (columns (5) to (8)). Because not all unit root tests reject non-stationarity of the explanatory variables in first differences, we also present the four models in second differences (columns (9) to (12)). However, for women the AR(2)-test is highly significant (with a p-value of 0.000 for the difference GMM-estimator, and 0.002 for the system GMM-estimator), which is a clear indicator that the model in second differences is misspecified for women, so we only present these results for completeness.

We observe that the coefficients of mortality are positive and highly significant for men. They suggest that expenditures for men in their last year of life are between 6 and 14 times as high as for the average sickness fund member. These estimates confirm the "red-herring" hypothesis and are roughly in line with findings from previous studies. E.g., Lubitz, Beebe, and Baker (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. For women, the coefficients are positive, but usually smaller and not always significant.

Longevity, measured by the predicted value of the 5-year survival rate, has a positive and always significant impact on HCE, although the size of the coefficient varies according to the specification. A value of 12, which seems to be a lower bound, suggests that an increase in the 5-year survival rate by 5 percentage points (which occurred for men over 70 and for women between 75 and 85 from 1997 to 2009) raises real daily per-capita HCE by roughly 10 per cent.

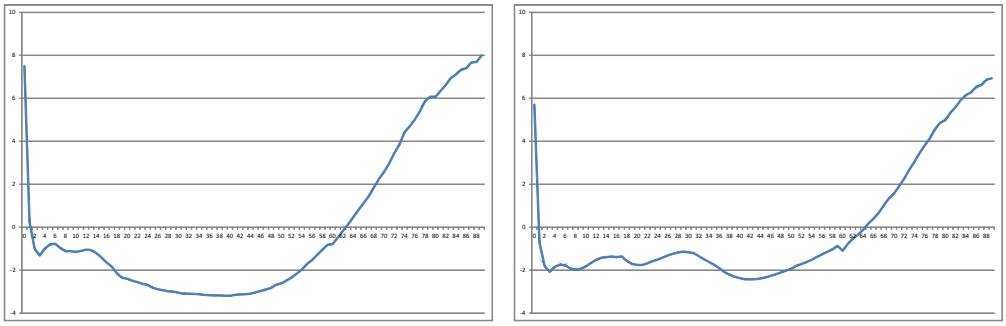
Table 4: Regression Results, dep. variable: daily HCE

	Men											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	level	level	level	level	Δ	Δ	Δ	Δ	Δ^2	Δ^2	Δ^2	Δ^2
GMM			Dif.	Sys.			Dif.	Sys.			Dif.	Sys.
$MORT$	**68.26**	**58.30**	**75.56**	**37.25**	**60.86**	**56.22**	**83.78**	**77.18**	**51.28**	**42.41**	**58.51**	**64.66**
	(.000)	**(.000)**	**(.000)**	**(.000)**	**(.000)**	**(.000)**	**(.000)**	**(.000)**	**(.000)**	**(.000)**	**(.000)**	**(.000)**
$SR5$		**36.45**	**33.46**	**14.23**		**13.83**	**12.46**	**12.08**		**21.84**	**11.51**	**13.12**
		(.000)	**(.000)**	**(.000)**		**(.023)**	**(.018)**	**(.049)**		**(.000)**	**(.004)**	**(.006)**
HCE_{t-1}			**0.11**	**0.22**			-0.03	-0.02			**-0.32**	**-0.23**
			(.008)	**(.000)**			(.310)	(.592)			**(.000)**	**(.000)**
$AR(1)$			**(.000)**	**(.000)**			**(.000)**	**(.000)**			**(.000)**	**(.000)**
$AR(2)$			(.484)	(.627)			(.312)	(.308)			(.970)	(.149)
	Women											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	level	level	level	level	Δ	Δ	Δ	Δ	Δ^2	Δ^2	Δ^2	Δ^2
GMM			Dif.	Sys.			Dif.	Sys.			Dif.	Sys.
$MORT$	27.22	**26.24**	15.25	**41.38**	**33.64**	20.38	8.46	7.90	14.21	-3.07	-0.35	2.50
	(.070)	**(.002)**	(.245)	**(.000)**	**(.000)**	(.068)	(.431)	(.384)	(.054)	(.665)	(.962)	(.747)
$SR5$		**42.69**	**28.99**	**10.66**		**15.77**	**19.43**	**18.01**		**17.70**	**16.17**	**15.76**
		(.000)	**(.000)**	**(.000)**		**(.001)**	**(.000)**	**(.000)**		**(.000)**	**(.000)**	**(.000)**
HCE_{t-1}			**0.28**	**0.28**			**0.11**	**0.13**			**-0.29**	**-0.22**
			(.000)	**(.000)**			**(.000)**	**(.000)**			**(.000)**	**(.000)**
$AR(1)$			**(.000)**	**(.000)**			**(.000)**	**(.000)**			**(.000)**	**(.000)**
$AR(2)$			(.973)	(.861)			(.791)	(.697)			**(.000)**	**(.002)**

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

We now turn to the results of the age, cohort and time dummies. We present the graphs for the model without any additional variables to focus on how the intrinsic estimator disentangles the three effects. In Figure 1 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 89.

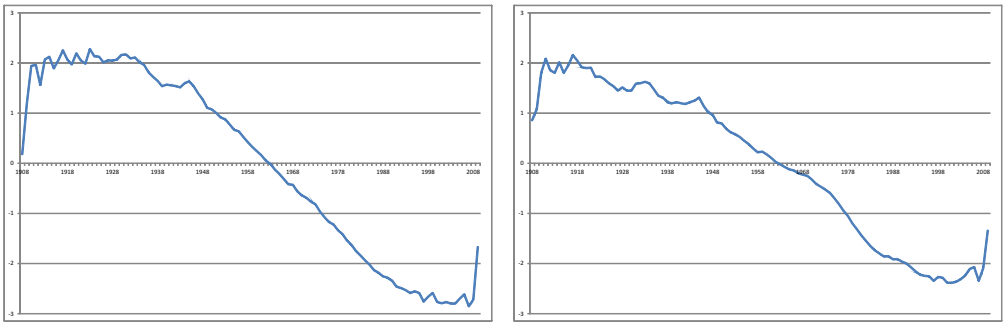
Figure 1: Graph of the age dummy coefficients



(a) Men (b) Women

The coefficients of the cohort dummies are declining except for the first and last few cohorts, which we observe only for a smaller number of years than the other cohorts, see Figure 2. The general pattern confirms the well-known fact that more recent cohorts are healthier at a given age and therefore need less medical care than older cohorts.

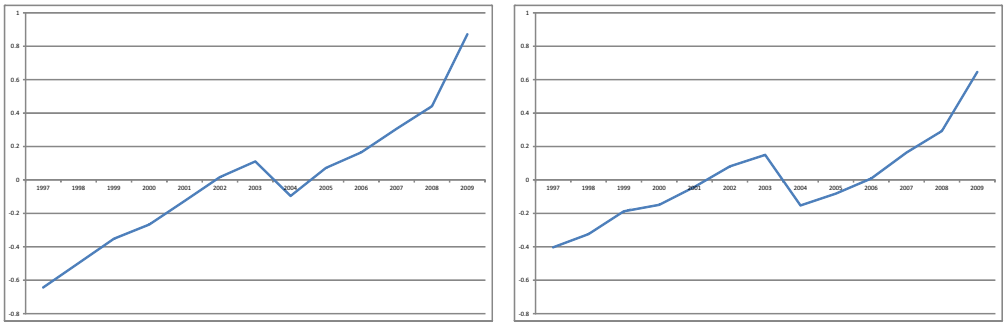
Figure 2: Graph of the cohort dummy coefficients



(a) Men (b) Women

Figure 3 shows the positive time trend for HCE. It also shows the impact of a major health care reform that took effect in 2004. Depending on the model specification, (model (1) to (12) in Table 4), the year dummies indicate an annual growth rate of 1.95 to 2.32 percent for men and 1.02 to 1.62 percent for women, which can be interpreted as the "pure time trend in real per-capita HCE", independent of demographic effects.

Figure 3: Graph of the year dummy coefficients



(a) Men (b) Women

We conclude that the hypotheses stated in Section 3 are supported by the results for both sexes. Since both the mortality rate and longevity have a (mostly) significant positive effect on HCE, the sign of the total effect of population ageing, which leads both to a decline in mortality and an increase in longevity, 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 Estimating the Demographic Effect on Health Care Expenditures

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 "12th coordinated population projection" (Statistisches Bundesamt 2009). In addition, the Office provided 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 survival rates. However, the German Statistical Office uses two different forecasts of mortality, the "most likely one" and one with an even stronger increase in longevity. In our simulations we shall use only the data from the former model.

In the following, we do not attempt to *forecast* the development of health care expenditures in Germany over the next decades. This would be a futile endeavour, because this depends to a great extent on political decisions. Instead, we are trying to measure the purely demographic impact on HCE by performing a counterfactual exercise in that we vary only the demographic factors, holding everything else constant at the 2009 level. For ease of interpretation, we divide the resulting values by the respective 2009 value of HCE, so that we can interpret the result as relative increase of HCE due to demographic change.

We proceed in three steps. We first consider only the effect of the reduction of mortality rates (without its impact on the survival rates and the age distribution). To do so, we calculate the age profiles of HCE and per capita HCE that would result from changing only the mortality rates for all age groups to their values in 2020, 2030, 2040, 2050 and 2060, using the regression results of the models with only $MORT$ as an additional explanatory variable besides age, year and cohort. Columns (1), (5) and (9) of the upper part of Tables 5 and 6 show that the well-known

"red-herring" effect is present in our data as well:[8] When the mortality rates decline in the way predicted for the next decades and everything else stays the same, the age profiles of HCE shift downwards because in each age bracket, fewer people are in their last year of life, so that per capita HCE decrease. However, the overall impact is rather modest: With the mortality rates of 2060, expenditures in 2009 for men would have been lower by at most 7.1 per cent, those for women by 3.2 per cent. Note that the calculations in this first step (columns 1, 5 and 9 in Tables 5 and 6) serve only as a benchmark for comparison because considering the change in mortality and ignoring the concomitant increase in survival rates of the elderly is inconsistent. Therefore we will not comment on these results in the following.

In the second step, we take into account that with falling mortality the 5-year survival rates must rise, which by itself would raise HCE. We therefore calculate the age profiles of HCE and per capita HCE that would result from changing both the mortality rates and the 5-year survival rates to their values in 2020, 2030, ... 2060, see the upper part of Tables 5 and 6 again. For men, the total change in HCE resulting from this variation lies between minus 2.3 per cent (column 7 of Table 5 and plus 12.6 per cent (column 2). For women, the total change is always positive and lies between 1 and 11.7 per cent (columns 4 and 2 of Table 6, respectively). Thus we see that, depending on the estimation method for this dynamic panel used, the decline in HCE due to lower mortality rates is either considerably mitigated or more than compensated by considering the concomitant increase in the 5-year survival rates of older population groups.

In the third step we also set the age distribution to their levels in 2020 through 2060. These results must be interpreted with caution because when we make use of the age dummy coefficients, we also have to decide how to treat the coefficients of the cohort dummies. However, there is no natural way to extrapolate the cohort effects because it is not known how healthy or unhealthy future cohorts will be. To make matters worse, there is no monotone trend in the cohort coefficients which could be easily extrapolated (see Figure 2). We therefore did not use any predicted (extrapolated) values for the cohorts but left them at their 2009 values, but this is not much more than the application of the Principle of Insufficient Reason. The results of this exercise can be found in the lower part of Tables 5 and 6. The numbers show that with the 2060 age composition (along with the 2060 mortality and survival rates), health care expenditures in 2009 would have been between 27 and 54 per cent higher for men and between 25 and 53 per cent higher for women, an effect that is considerably higher than the impact of mortality and survival rates alone. The second line from the bottom in each of the Tables 5 and 6 contains the results of converting the respective increases into annual growth rates, which can be interpreted as "growth in HCE due to demographic change". Considering both the changes in mortality and in 5-year survival rates, these numbers lie between .45 and .87 per cent for both sexes.

In the last line of Tables 5 and 6 we present the pure time trend in real per-capita HCE, independent of demographic effects, which is probably to a great extent due to medical progress. These annual growth rates lie roughly at or slightly above 2 per cent for men and between 1 and 1.5 per cent for women and are thus considerably larger than the purely demographic effect estimated above. If these two effects are added up, the resulting growth rates lie between 2.5 and 3 per cent for men and between 1.5 and 2.5 per cent for women, which is somewhat higher than common forecasts of the growth rate of per capita income in the ageing German population. Thus they suggest that demographic change and technical progress combined may after all present problems for the financing of health care in Germany.

[8] Because we consider the model in second differences to be misspecified for women, we did not calculate the age profiles and average HCE for these models, so columns (9) to (12) are missing for women.

Table 5: Relative values of per capita HCE when mortality rates and survival rates (and the age distribution) are set to their future values

	Men											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	level	level	level	level	Δ	Δ	Δ	Δ	Δ^2	Δ^2	Δ^2	Δ^2
GMM			Dif.	Sys.			Dif.	Sys.			Dif.	Sys.
$MORT$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$SR5$		✓	✓	✓		✓	✓	✓		✓	✓	✓
HCE_{t-1}			✓	✓			✓	✓			✓	✓
	Age distribution not adjusted											
2009	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	0.975	1.033	1.022	1.007	0.978	1.000	0.988	0.990	0.981	1.017	0.996	0.996
2030	0.960	1.061	1.044	1.016	0.964	1.003	0.984	0.987	0.970	1.033	0.996	0.997
2040	0.948	1.085	1.062	1.022	0.954	1.007	0.981	0.984	0.961	1.046	0.997	0.998
2050	0.938	1.107	1.078	1.029	0.944	1.010	0.978	0.983	0.953	1.057	0.997	0.999
2060	0.929	1.126	1.093	1.034	0.936	1.012	0.977	0.981	0.946	1.068	0.998	1.000
	Age distribution adjusted to 2060											
2009	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.078	1.152	1.139	1.119	1.081	1.110	1.095	1.097	1.085	1.131	1.104	1.104
2030	1.137	1.286	1.260	1.218	1.143	1.201	1.173	1.177	1.151	1.243	1.190	1.191
2040	1.184	1.419	1.378	1.311	1.193	1.284	1.240	1.246	1.206	1.351	1.267	1.269
2050	1.190	1.505	1.450	1.361	1.203	1.324	1.264	1.273	1.220	1.414	1.301	1.304
2060	1.184	1.554	1.491	1.383	1.199	1.341	1.273	1.282	1.218	1.446	1.314	1.317
%-growth rate demographic	0.33	0.87	0.79	0.64	0.36	0.58	0.47	0.49	0.39	0.73	0.54	0.54
%-growth rate time trend	1.95	2.32	2.26	2.14	1.96	2.10	2.05	2.06	1.98	2.20	2.08	2.08

Table 6: Relative values of per capita HCE when mortality rates and survival rates (and the age distribution) are set to their future values

	Women							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	level	level	level	level	Δ	Δ	Δ	Δ
GMM			Dif.	Sys.			Dif.	Sys.
$MORT$	✓	✓	✓	✓	✓	✓	✓	✓
$SR5$		✓	✓	✓		✓	✓	✓
HCE_{t-1}			✓	✓			✓	✓
	Age distribution not adjusted							
2009	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	0.991	1.048	1.033	1.001	0.989	1.014	1.023	1.021
2030	0.986	1.084	1.059	1.003	0.983	1.026	1.040	1.037
2040	0.982	1.116	1.081	1.006	0.977	1.036	1.056	1.051
2050	0.978	1.145	1.101	1.008	0.972	1.045	1.069	1.064
2060	0.974	1.170	1.118	1.010	0.968	1.053	1.081	1.075
	Age distribution adjusted to 2060							
2009	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.058	1.126	1.108	1.070	1.056	1.085	1.095	1.093
2030	1.107	1.237	1.202	1.131	1.103	1.159	1.176	1.172
2040	1.160	1.375	1.317	1.200	1.154	1.246	1.276	1.269
2050	1.191	1.487	1.408	1.246	1.183	1.310	1.351	1.342
2060	1.192	1.532	1.440	1.256	1.182	1.327	1.374	1.363
%-growth rate demographic	0.34	0.84	0.72	0.45	0.33	0.56	0.62	0.61
%-growth rate time trend	1.02	1.62	1.46	1.14	1.01	1.26	1.34	1.32

7 Conclusions and Caveats

In this paper, we have used 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 5-year survival rates. We believe that this effect mirrors the medical profession's willingness to perform expensive treatments on elderly patients if the patients can be expected to live long enough to enjoy the effects of the treatment.

The results of the simulations based on the regression coefficients show that if past trends continue, per-capita health care expenditures would rise by between 1.5 and 2 per cent per year even without demographic change. 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 mor-

tality rates are added. The effect of rising longevity can not be ignored, either. One way to take it into account is to include a measure of age-specific survival rates. Altogether, the effect of demographic change on health expenditures is estimated to be similar to an annual growth rate between .5 and .9 per cent, depending on which estimator is used.

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 sex group averages instead of individual expenditure data, the well-known effect of time-to-death on HCE expenditures is accounted for only in an 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 may raise 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 survival rates themselves are influenced by HCE and therefore endogenous. We circumvent the problem of endogeneity for $SR5$ by using its predicted value instead of $SR5$ as such. For $MORT$, possible endogeneity is accounted for in the dynamic panel models (estimated by GMM) by using only lagged values as instruments.

In addition, for the models not estimated by GMM, one may also argue that, unlike in individual data, for group averages the causal effect of HCE on mortality should not be too strong. It does not seem likely that the correlation of the variation in HCE and $MORT$ is caused primarily by tight rationing against a particular age-sex group as a whole in a certain year by all physicians leading to a higher mortality rate, but rather by a higher mortality rate of an age-sex group causing higher expenditures. For the models not estimated by GMM, 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 longevity alongside a fall in mortality rates – as such will increase health expenditures, and the answer to this question is a clear "yes". Moreover, independent of the specification, the 5-year survival rate always has a positive impact on health care expenditures so that for Germany a Eubie Blake effect indeed exists.

Appendix

The following Tables 7 to 9 provide the unit root tests for the variables HCE, $MORT$ and $SR5$.

Table 7: Unit root tests, dep. variable: daily HCE

	Men									
	HCE		ΔHCE		ΔHCE		$\Delta^2 HCE$		$\Delta^2 HCE$	
time trend	yes		no		yes		no		yes	
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Harris-Tsavalis $\bar{t}$	0.316	0.000	0.202	0.000	0.486	0.951	-0.124	0.000	-0.093	0.000
Im-Pesaran-Shin $W_{\bar{t}}$	-2.582	<0.01	-3.507	<0.01	-3.679	<0.01	-4.844	<0.01	-4.756	<0.01
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 1)	-1.356	0.088	-16.022	0.000	-10.518	0.000	-27.355	0.000	-18.079	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 2)	-1.745	0.041	-15.666	0.000	-9.788	0.000	-25.103	0.000	-17.280	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 3)	-1.339	0.090	-11.258	0.000	-5.678	0.000	-17.004	0.000	-9.909	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 4)	-44.188	0.000	-38.012	0.000	-2.502	0.006	-12.344	0.000	-9.652	0.000
	Women									
Harris-Tsavalis $\bar{t}$	0.355	0.001	0.188	0.000	0.404	0.308	-0.159	0.000	-0.125	0.000
Im-Pesaran-Shin $W_{\bar{t}}$	-2.958	<0.01	-3.657	<0.01	-4.027	<0.01	-5.192	<0.01	-5.018	<0.01
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 1)	-5.460	0.000	-16.221	0.000	-14.615	0.000	-29.605	0.000	-19.986	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 2)	-7.541	0.000	-15.188	0.000	-10.013	0.000	-21.788	0.000	-13.408	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 3)	-3.702	0.000	-11.984	0.000	-2.270	0.012	-14.892	0.000	-66.537	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 4)	-36.543	0.000	-45.483	0.000	-1.461	0.072	-12.543	0.000	-10.228	0.000

IPS-test with lags contains optimal number of lags (up to the maximal number of lags given in parenthesis) according to BIC.

Table 8: Unit root tests, dep. variable: $MORT$

	Men									
	$MORT$		$\Delta MORT$		$\Delta MORT$		$\Delta^2 MORT$		$\Delta^2 MORT$	
time trend	yes		no		yes		no		yes	
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Harris-Tsavalis $\bar{t}$	1.062	1.000	0.378	0.000	0.987	1.000	-0.782	0.000	-0.702	0.000
Im-Pesaran-Shin $W_{\bar{t}}$	0.477	>0.10	-1.538	>0.10	-3.924	<0.01	-6.493	<0.01	-6.516	<0.01
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 1)	26.843	1.000	9.075	1.000	-15.452	0.000	-42.604	0.000	-31.978	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 2)	28.353	1.000	12.626	1.000	-13.437	0.000	-39.433	0.000	-30.945	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 3)	28.149	1.000	12.995	1.000	-10.137	0.000	-35.249	0.000	-25.113	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 4)	25.275	1.000	17.103	1.000	-9.912	0.000	-34.699	0.000	-4.021	0.000
	Women									
Harris-Tsavalis $\bar{t}$	1.144	1.000	0.793	0.934	1.072	1.000	-0.600	0.000	-0.390	0.000
Im-Pesaran-Shin $W_{\bar{t}}$	1.327	>0.10	-0.740	>0.10	-2.983	<0.01	-5.045	<0.01	-5.273	<0.01
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 1)	31.784	1.000	13.085	1.000	-6.146	0.000	-26.354	0.000	-18.345	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 2)	32.618	1.000	19.735	1.000	-2.449	0.007	-22.604	0.000	-16.391	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 3)	31.344	1.000	19.887	1.000	-2.364	0.009	-21.566	0.000	-14.311	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 4)	26.890	1.000	20.684	1.000	-1.079	0.140	-18.747	0.000	-3.986	0.000

IPS-test with lags contains optimal number of lags (up to the maximal number of lags given in parenthesis) according to BIC.

Table 9: Unit root tests, dep. variable: daily $SR5$

	Men									
	$SR5$		$\Delta SR5$		$\Delta SR5$		$\Delta^2 SR5$		$\Delta^2 SR5$	
time trend	yes		no		yes		no		yes	
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Harris-Tsavalis $\bar{t}$	0.943	1.000	0.617	0.000	1.0488	1.000	-0.480	0.000	-0.395	0.000
Im-Pesaran-Shin $W_{\bar{t}}$	-0.205	>0.10	-0.899	>0.10	-3.170	<0.01	-4.052	<0.01	-3.856	<0.01
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 1)	17.368	1.000	5.993	1.000	-8.429	0.000	-19.511	0.000	-10.829	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 2)	17.077	1.000	6.240	1.000	-7.698	0.000	-18.645	0.000	-9.074	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 3)	15.217	1.000	5.904	1.000	-5.477	0.000	-13.483	0.000	-10.088	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 4)	0.987	0.838	1.915	0.972	-5.940	0.000	-13.653	0.000	-9.422	0.000
	Women									
Harris-Tsavalis $\bar{t}$	0.981	1.000	0.897	1.000	1.086	1.000	-0.519	0.000	-0.264	0.000
Im-Pesaran-Shin $W_{\bar{t}}$	0.211	>0.10	-0.187	>0.10	-3.065	<0.01	-3.704	<0.01	-3.579	<0.01
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 1)	20.869	1.000	11.922	1.000	-7.553	0.000	-16.465	0.000	-8.743	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 2)	20.519	1.000	11.333	1.000	-7.368	0.000	-16.040	0.000	-7.970	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 3)	18.807	1.000	11.074	1.000	-8.300	0.000	-11.062	0.000	-3.903	0.000
Im-Pesaran-Shin $W_{\bar{t}}$ (lag up to 4)	11.269	1.000	9.930	1.000	-8.413	0.000	-11.404	0.000	-8.151	0.000

IPS-test with lags contains optimal number of lags (up to the maximal number of lags given in parenthesis) according to BIC.

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