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# A Life Course Perspective on the Income-to-Health Relationship: Macro-Empirical Evidence from Two Centuries

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## Zusammenfassung / Abstract

The epidemiological literature discusses two contrary hypotheses that describe life course variations in the income-to-health relationship: the cumulative advantage and the age as leveller hypothesis. The present study investigates both hypotheses at a macroeconomic level. It asks whether increases in per capita income improve population health and whether the improvements differ across population age-groups. The analysis relies on unbalanced panel data from 20 countries and up to 211 years. It applies an error correction and common factor framework to investigate the long-run relationships between income and age-specific survival rates. A significant effect of per capita income on survival rates is found for middle ages but not for very young and old age-groups. Thus, while the cumulative advantage theory describes the transition from young to middle age-groups, the transition from middle to old age-groups corresponds to the age as leveller mechanism.

**JEL-Klassifikation / JEL-Classification:** J11; C22; I15;

**Schlagworte / Keywords:** Population Health; Economic Development; Panel Time Series Analysis; Cumulative Advantage; Age as Leveller

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# 1. Introduction

The literature on life course epidemiology has presented much evidence that the income-to-health relationship varies during the years of life. Studies have established two contrary hypotheses on how the relationship may change: the *cumulative advantage* and the *age as leveller* hypothesis (Dupre, 2007).

The first hypothesis, the *cumulative advantage* hypothesis, states that the effect of income on health increases with age. It has a theoretical foundation due to the accumulation of health-related risks and benefits. If income is a healthy thing, its impacts accumulate during the life time in which the income is available. Consequentially, the effects of income on health should be stronger at older than at younger ages (see Ross and Wu, 1996; Hertzman et al., 2001; Willson et al., 2007). In contrast to this accumulation effect, the second hypothesis, the *age as leveller* hypothesis, captures the contrary but frequent empirical finding that the income-to-health relationship declines or even diminishes at older ages (see e.g. House et al., 1994; Beckett, 2000; Mishra et al., 2004).

Life course variations in the income-to-health relationship have been investigated in micro-level studies. However, these studies are the target of potential critiques. On the one hand, they demonstrate that income differences coincide with health differences across individuals but they do not consider that increasing an individual's income may improve that individuals health yet simultaneously worsen the health of others by reallocating medical resources. Therefore, these micro-level studies may capture the selection of available medical resources for better-endowed society members rather than an equilibrium relationship (cf. Acemoglu and Johnson, 2007, p. 926). On the other hand, they do not distinguish a pure income effect from the importance of the relative economic position within the society. In this regard, Lynch et al. (2000) emphasize the perception of place in the social hierarchy arguing that, due to psychosocial factors, the income rank is the important health determinant and not income itself.

To meet this critique of relative income and rank, it is worth considering life course variations at an aggregate level. To my knowledge, however, the macro-empirical literature still lacks the life course analysis of the income-to-health relationship. To narrow this gap, and to test the *cumulative advantage* versus the *age as leveller hypothesis*, this study conducts a cross-age comparison of survival conditions at a country level.

Several macro-empirical studies analyse the effect of income on population health but they do not consider age-variations in the relationship (see Goldstein, 1985; Pritchett and Summers, 1996; Swift, 2011). However, data on mortality that can be linked to the corresponding age-groups are available for a notable number of mostly developed countries. These data allow an effective analysis of the income-to-health relationship during the life course of the population. The present study takes advantage of the age dimension in the available data and estimates the effect of per capita income on survival rates successively for all age-groups.

Data on survivability as well as on per capita income are available for long periods of time. The present empirical analysis relies on unbalanced panel data. They contain a large number of periods, ranging from 52 to 211 years per country but cover only 20 countries because the availability of detailed data is limited. The availability of long-term data has several advantages. On the one hand, it allows a time-series perspective in order to draw conclusions on causality. On the other hand, it ensures that sufficient variation is observable in all variables; in particular, the survival rates of young age-groups have shown substantial growth in early periods of the panel but they haver nearly reached 100% in recent years.

The empirical framework applied in this study is composed of a common factor and a cointegration approach. It accounts for the impacts of common shocks and common stochastic trends and it reflects that both survival rates and per capita income are non-stationary. Specifically, the empirical investigation applies the Westerlund (2007) test for cointegation, the Pesaran (2006) common correlated effects estimation approach, and error-correction-based exogeneity tests similar to those applied by Canning and Pedroni (2008) and Eberhardt et al. (2013).

This study finds that increases in per capita income affect survivability of middle age-groups. It can not detect significant effects of per capita GDP on the survival rates of the very young or on survival rates of old age-groups above 80. The relationship between per capita income and age-specific survival rates takes a hump-shaped form. Thus, macro-empirical evidence for the *cumulative advantage hypothesis* is found for the transition from young to middle ages, whereas the transition from middle to old ages corresponds to the *age as leveller* mechanism. The findings are robust to the use of conditional survival rates, to country outliers, to modifications of the estimation framework, and to gender-specific differences.

The present work is closely linked to two bodies of empirical works. The first are the micro-level studies that investigate socio-economic differences in health from a life course perspective.

These studies take a controversial approach discussing empirical evidence for both hypotheses (see Ross and Wu, 1996; Beckett, 2000; Mishra et al., 2004; Dupre, 2007; Willson et al., 2007). One study, namely House et al. (1994) is of particular interest here as it provides quite similar results to the findings in this study. The authors analyse the separate effects of education and income on self-reported health and find evidence for both the *cumulative advantage* hypothesis during youth and middle adulthood and the *age as leveller* mechanism during late adulthood and senior ages.

The second body of literature that is closely related to this study is the macro-empirical literature, which estimates the effect of per capita income on population health. Specifically one study has much in common with the present analysis because it uses similar data and a related econometric methodology: Swift (2011) considers 13 OECD countries for periods ranging from 1820–2001 to 1920–2001 and finds positive effects of GDP per capita on life expectancy at birth for most but not all countries in the sample. However, Swift (2011) does not consider age differences in population health.

The present study is organized as follows. Section 2 motivates the analysis and provides a theoretical background. Section 3 presents the empirical strategy and describes the data. Section 4 presents the results. Section 5 summarizes and concludes. Additional findings including robustness checks are contained in an appendix.

## 2. Motivating Background

### 2.1. A Life Course Perspective on the Income-to-Health Relationship

Both the *cumulative advantage* and the *age as leveller* hypothesis have their motivation in the temporal ordering of health-related factors and their outcome measures. Both are supported with empirical evidence in micro-level studies.

The theory of *cumulative advantage* is attributed to Merton (1968) and emphasizes the increasing divergence with age in scientific careers (Ross and Wu, 1996). Later, it has also been applied to life course patterns in health trajectories. Brunner et al. (1999) show that the accumulation of cardiovascular risks begins in childhood and continues in adulthood. Power and Hertzman (1997) and Hertzman et al. (2001) illustrate that both contemporaneous and life course factors together generally explain health outcomes. Specifically concerning the effects of education and income, Ross and Wu (1996) analyse respondents of a U.S telephone

interview survey and find that the disparities in self-related health created by socio-economic differences diverge with age. Similar evidence is provided by Willson et al. (2007).

However, many and even a majority of empirical studies find evidence contradicting the *cumulative advantage* hypothesis: health disparities provoked by income often decline or diminish with age - a phenomenon that is named the *age as leveller* hypothesis (cf. Beckett, 2000; Dupre, 2007). In this regard, Mishra et al. (2004) as well as Jatrana and Chan (2007) claim that health differentials across socio-economic conditions are more evident across mid-age than across older age-groups. Woo et al. (2000) even find that absolute income is not an important factor contributing to mortality and morbidity of the elderly population aged 70 years and above.

While the *cumulative advantage* hypothesis is theoretically well established due to the accumulation of health-related risks and benefits, the *age as leveller* phenomenon lacks such a clear and unique rationale. The most prominent explanation for the *age as leveller* hypothesis is *selective mortality* (see Beckett, 2000; Dupre, 2007; Rohwer, 2016). Typically, frail members of the population that are endowed with both low income and poor health die relatively early. The remaining older society members are characterized by good health associated with high life expectancy and by relatively high income. Their health status is less sensitive to income gains and losses.

An additional and complementary reason for the *age as leveller* hypothesis can be found in a continuative literature that explores the determinants of extreme longevity. Willcox et al. (2007) stress that typical determinants of longevity and healthy ageing are long-term calorific restrictions, temporary negative energy balances, and an active but stress-free life style. Typically, such factors are linked to economic scarcity rather than to good income. Hence, these factors may be the reason for why economic growth can also weaken the conditions for longevity and healthy ageing so that they provide a potential explanation for the *age as leveller* mechanism.

## 2.2. The Life Course Framework from a Macroeconomic Perspective

Compared to the related micro-level studies that exploit health-differential over individual life courses, the present study asks whether economic growth generates increases in survivability and whether these increases differ across population age-groups.

Suppose that income causes good health; people are healthier and live longer in rich countries than in poor countries, people are healthier and live longer today compared to poorer times before (cf. Deaton, 2003). Economic growth can bring many health-related benefits, through increasing consumption possibilities, through improving the provision of health care goods, or through reducing the risk of exposure to episodes of economic scarcity. The ability to absorb these benefits and to transform them into better health may vary across age-groups.

**Figure 1:** The impacts of economic growth on health from a life course perspective

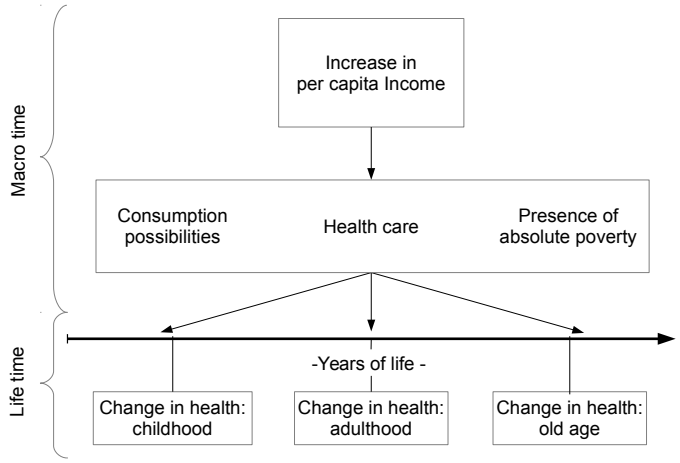



Figure 1 illustrates the potential life course impacts of economic growth. It incorporates two time dimensions (cf. Elder, 1975). First, a macroeconomic time at which improvements in health conditions are rendered by increases in per capita income. Second, the life time of individuals and their age-groups during which the absorbance of improved health conditions and their transmission towards improved health outcomes occurs. The changes in health outcomes can then be observed and compared across population age-groups.

According to the *cumulative advantage* hypothesis growth-induced improvements in health should be stronger for older than for younger age-groups because older age-groups should have had more opportunities to collect the advantages of increases in income during their relatively long lives. Old ages need comparatively more health care than young ages to maintain an acceptable health status and to ensure survival. Health care is costly and the provision of health care services is facilitated by economic growth. Consider, for example, that an increase in per capita income has made a specific medical treatment available that raises the probability of survival. The probability that this treatment will be demanded by a

specific society member increases with that member's age, implying that the health effect of per capita income is stronger for older age-groups.

In contrast, if the *age as leveller* hypothesis is valid at a macro level, older age-groups should gain less from economic growth than younger groups. Consider *selective mortality*; in particular frail members of the population gain from economic growth in terms of their health. However, they may still die relatively early and the observable income-to-health relationship may diminish with age when comparing middle with older age-groups.

Another reason for a diminishing effect at higher ages is the unequal distribution of growth benefits across population age-groups. Older age-groups may not have access to the gains achieved in economic growth because thy do not participate actively in the labour market. However, modern societies have invested much in public health care and pension systems during the time span that is covered by the present data set (cf. Preston, 1984; House et al., 1994). These social reforms have certainly improved the access to health benefits induced by economic growth for the older population.

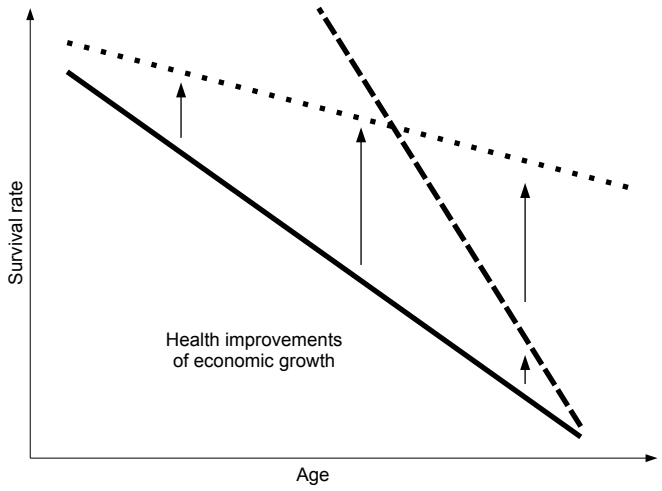
In conclusion, there are many intuitive reasons that the effect of per capita income on health varies across population age-groups. Both the *cumulative advantage* and the *age as leveller* hypothesis find their theoretical motivations even at a macro-economic level. However, it remains an empirical question as to how these variations manifest themselves.

### 2.3. Age-specific Population Health

In order to analyse health differences across age-groups at a macro-economic level, the present study relies on survival rate estimates. Figure 2 plots stylized survival rates as functions of age and illustrates how they may respond to changes in per capita income. While the lower continuous line depicts survivability before an increase in per capita income occurs, both the dotted and dashed lines illustrate the potential shifts in survival rates due to the increase in income. Assuming validity of the *cumulative advantage* hypothesis, the dotted line is flatter than the solid line because younger ages benefit less from economic growth in terms of survivability than older ages. In contrast, assuming that the *age as leveller* hypothesis applies, the dashed line is steeper, indicating that older ages gain less from economic growth.

Survival rate estimates are calculated from death counts. They specify the number of people out of a population that survive to a particular age $z$, or, to put it differently, to their

**Figure 2:** Stylized impacts of economic growth on age-specific survival rates




zth birthday.[1] From a life course perspective they proxy the health conditions to which a representative member of the population is exposed from birth to the age $z$.

The following empirical analysis considers all survival rates of ages 1 to 100. For reasons of clarity, some specific survival rates, namely the survival rates of ages 1, 40, and 80, are emphasized at particular stages of the empirical analysis.

# 3. Empirical Strategy and Data

## 3.1. Empirical Strategy

This study successively investigates the long-run relationships between per capita income and age-specific survival rates. Differences in the investigated relationships would suggest that the income-to-health relationship changes over the years of life. By reason of comparability, each age-specific investigation is applied within the same estimation framework that is explained in the following.

Empirical studies commonly focus on instrumental variables in order to address the potential endogeneity of macroeconomic variables. However, several studies doubt whether it is possible to find convincing instruments in a macro-empirical context (see Durlauf et al., 2005; Bazzi and Clemens, 2009). In addition, instrumentation is impossible if the underlying rela-

[1] The study mainly focuses on unconditional survival rates that capture survivability from birth to the age $z$. Appendix D.3 discusses the use of unconditional rates and presents evidence that the results of this study hold whether conditional or unconditional survival rates are considered.

tionship is heterogeneous across countries (Eberhardt and Teal, 2013). On these grounds, this study avoids an instrumental variable approach but employs a panel time series framework.

One part of the framework is a common factor approach that is intended to account for the common stochastic evolution and for omitted components in the relationship between income and survivability. It meets the empirical fact that both survival rates and GDP per capita have evolved similarly across countries and are cross-sectionally dependent.[2]

Intuitively, the common factors may be classified into two categories: diffused technological progresses and common shocks. The common technological evolution can be understood as cross-country spillovers of technological developments that affect survival rates through improved medical care and per capita income through the transmission of productive knowledge. Arguing that mortality reductions tend to depend more on scientific and technological advances than on income increases, Cutler et al. (2006) implicitly propose that account should be taken for technological progresses in the income-to-health relationship. Similar to the empirical framework presented here, Eberhardt et al. (2013) use a common factor framework in order to account for the cross-country spillovers of R&D activities.

Beside the influences of technological progress, cross-country dependencies can also be driven by common shocks that affect all or at least a limited number of sample countries. These shocks may have economic as well as mortality related impacts. Examples of such shocks are wars and flu pandemics that temporarily reduce production capacities and increase death rates across countries.

Consider panel data for N countries, with a time dimension T, the common factor model can be described as

$$\begin{aligned} S_{xit} &= \alpha_{1xi} + \beta_{xi} Y_{it} + \lambda'_{1xi} \mathbf{f}_t + \epsilon_{xit} \\ Y_{it} &= \alpha_{2i} + \lambda'_{2i} \mathbf{f}_t + \nu_{it} \end{aligned} \tag{1}$$

where $i$ is the country index and $t$ the time index. The index $x$ denotes the year of age. Thus, $S_{xit}$ is the survival rate of the particular age $x$ (SurRateX). $\alpha_{1xi}$ and $\alpha_{2i}$ are country-specific intercepts. $Y_{it}$ is the natural logarithm of per capita GDP (lnGDPpc).[3] $\mathbf{f}_t$ is a set of common factors that affect both age-specific survival rates and per capita GDP with heterogeneous

[2] Cross-sectional dependence in the series is detected by the Pesaran (2004) test. A description of the test and the test results can be found in Appendix B.

[3] The log-level form of the income-to-survivability relationship is motivated by the results of several studies such as Preston (1975); Goldstein (1985); Deaton (2003). It accounts for the fact that the effect of income decreases as income increases. It is also motivated by data characteristics. Taking the logarithms decreases the skewness of the probability density functions of GDP per capita but, in contrast, would increase the skewness of the survival rates.

factor impacts $\lambda_{1xi}$ and $\lambda_{2i}$. $e_{xit}$ and $\nu_{it}$ are error terms. The common factor framework allows the common factors to follow non-stationary processes, to have heterogeneous impacts across countries, and to affect both survival rates and GDP per capita simultaneously.

In addition to cross-sectional dependence, an important data property in the present data set is variable non-stationarity. It requires a test to be conducted for cointegration between GDP per capita and survival rates in order to avoid spurious regression results (see e.g. Granger and Newbold, 1974; Engle and Granger, 1987).[4] Testing for cointegration further ensures that the estimations are robust to a broad class of omitted variables (Pedroni, 2007). This is a highly auxiliary fact as reliable data of relevant control variables are simply not available for the high number of early time periods.

Specifically, I employ the Westerlund (2007) methodology to test for cointegration between per capita GDP and survival rates. It relies on an unrestricted conditional error correction representation that is given by

$$\Delta S_{xit} = \alpha_{xi} + \kappa_{xi} S_{xit-1} + \phi_{xi} Y_{it-1} + \phi_{xi}^{f} f_{t-1} + \sum_{j=-q_i}^{p_i} \gamma_{xij} \Delta S_{xit-j} + \sum_{j=-q_i}^{p_i} \nu_{xij} \Delta Y_{it-j} + \epsilon_{xit} \quad , \quad (2)$$

where $\kappa_i$ is the error correction parameter that measures the adjustment of $S_{xit}$ to deviations from the long-run equilibrium relationship. The parameters $\gamma_{xij}$ and $\nu_{xij}$ account for short-run dynamics.

Based on the estimates of $\kappa_i$, the Westerlund (2007) test computes four semi-parametric test statistics. Two of them are group statistics that indicate whether there is cointegration between pairs of variables for at least one country in the sample. The other two build on pooled estimations and, thus, test whether there is cointegration for the panel as a whole. In the presence of country heterogeneity in the relationships considered, group estimates lead to a more accurate representation of the underlying relationship as they rely on individual slope coefficients (see Pedroni, 1996; Haque et al., 1999; Eberhardt and Presbitero, 2015). To account for common factors, Westerlund (2007) uses a methodology to compute and bootstrap critical values that is similar to the methodology presented in Chang (2004). In that way, the Westerlund (2007) test offers common factor robust p-values that indicate whether to maintain or reject the hypothesis of no error correction.

[4] Appendix C presents unit root test results that support the hypothesis of non-stationary variables.

The Westerlund (2007) test is applied to all pairwise relationships between GDP per capita and one of the age-specific survival rates. If cointegation is detected for a particular age-specific relationship, while it has to be rejected for another, we can conclude that the income-to-health relationship changes over the years of life.

In order to present quantifying estimates of the relationship between per capita income and survival rates, the present approach relies on a common correlated effects (CCE) estimation framework. In order to filter out the differential individual-specific impacts of common factors, the CCE framework augments regressions with variable cross-section averages. Advantageously, the CCE estimators are estimated by ordinary least squares. This allows the Pesaran (2004) test on cross-section dependence to be applied to the estimation residual and thus permits an investigation as to whether the common correlated effects framework is powerful in resolving existing cross-sectional dependence in the variables.

Several variants of the CCE framework are considered and then evaluated regarding their efficiency in resolving cross-sectional dependence. The first variant that is applied is the CCE mean-group estimator (CCEMG) proposed by Pesaran (2006). It is given by

$$S_{xit} = \alpha_{xi} + \beta_{xi} Y_{it} + \eta_{1xi} \overline{S}_{xt} + \eta_{2xi} \overline{Y}_t + \epsilon_{xit} \quad , \tag{3}$$

where $\overline{S}_{xt}$ and $\overline{Y}_t$ are the cross-sectional averages of both the age-specific survival rate and GDP per capita. The CCEMG estimates the relationship depicted in Equation 3 for each country separately and then averages the individual long-run coefficients over all countries. The standard errors are calculated non-parametrically following Pesaran and Smith (1995).

In addition to the CCE mean-group estimator, the CCE pooled estimator (CCEP) of Pesaran (2006) is also concerned. It investigates the long-run relationship in the panel as a whole. Further, the dynamic CCE mean-group estimator (DCCEMG) suggested by Chudik and Pesaran (2015) is adopted. It augments the estimations with lagged values of the dependent variable and with additional lagged values of cross-section averages.[5] The DCCEMG is an autoregressive specification of the CCE framework that allows the independent variable per capita GDP to be weakly exogenous. Following Chudik et al. (2015), it is possible to account for a potential simultaneity bias in the estimated relationship. All CCE models that

[5] Specifically, the DCCEMG is given by $S_{xit} = \alpha_{xi} + \phi_{ix} S_{xi,t-1} + \beta_{xi} Y_{it} + \sum_{k=0}^{p} (\eta_{1xi,t-k} \overline{S}_{x,t-k} + \eta_{2xi,t-k} \overline{Y}_{t-k}) + \epsilon_{xit}$. The long-run coefficients are calculated as $\frac{\sum_i \beta_{xi}}{(1-\sum_i \phi_{xi})}$.

are adopted in the empirical investigation are estimated with and without a country-specific linear trend term.

Within the literature on economic growth, several studies claim that increases in survivability affect per capita income.[6] Therefore, they provide evidence for reverse causality in the income-to-health relationship and point to a potential simultaneity bias in the estimated coefficients. On theses grounds, the present study analyses the direction of causality in the estimated relationships. Given the dynamic estimation frameworks, an analysis is conducted to test whether the assumption of weakly exogenous regressors holds.

I follow Canning and Pedroni (2008) as well as Eberhardt and Teal (2013) and apply error-correction-based causality tests. The tests are applied to the particular age-specific relationships for which significant cointegration has been detected. The tests build on the Granger Representation theorem (Engle and Granger, 1987) and consist of country-specific dynamic error-correction models, where the coefficients capturing the long-run relationship are restricted to those previously obtained by the various CCE estimation frameworks. Common factors are represented by variable cross-sectional averages and are included in both the long-run and the short-run relationships (cf. Eberhardt and Teal, 2013; Gengenbach et al., 2015).

The dynamic error correction model takes the form

$$\Delta S_{xit} = c_{1xi} + \lambda_{1xi}\hat{e}_{xi,t-1} + \sum_{j=1}^{p_{1i}} \gamma_{1xi,t-j}\Delta S_{xi,t-j} + \sum_{j=1}^{p_{1i}} \nu_{1xi,t-j}\Delta Y_{i,t-j} + \psi'_{1xi}\Gamma_1 + \epsilon_{1xit} \quad (4)$$

$$\Delta Y_{it} = c_{2xi} + \lambda_{2xi}\hat{e}_{xi,t-1} + \sum_{j=1}^{p_{2i}} \gamma_{2xi,t-j}\Delta S_{xi,t-j} + \sum_{j=1}^{p_{2i}} \nu_{2xi,t-j}\Delta Y_{i,t-j} + \psi'_{2xi}\Gamma_2 + \epsilon_{2xit} \quad (5)$$

where $\hat{e}$ is the disequilibrium term which measures the deviation from the equilibrium relationship and which implements the restrictions imposed on the long-run coefficients. The disequilibrium is given by $\hat{e}_{2i,t-1} = S_{xit} - \hat{\alpha}_{xi} - \hat{\beta}_{xi}Y_{it} - \hat{\eta}_{1xi}\overline{S}_{xit} - \hat{\eta}_{2xi}\overline{Y}_{it}$, where the coefficients denoted with hats are those that are obtained by a particular estimation framework, as described above.[7] In Equations 4 and 5, the coefficients $\lambda_{1xi}$ or $\lambda_{2xi}$ capture the adjustment

[6] The debate on this issue is fed by Acemoglu and Johnson (2007) who even find a negative effect of mortality reductions on per capita income. Also Ashraf et al. (2008) doubt the existence of an positive effect of health. However, a significant effect of mortality on GDP is documented by many studies such as Arora (2001, 2005); Bhargava et al. (2001); Bloom et al. (2004, 2014); Swift (2011); Lorentzen et al. (2008).

[7] More precisely, the disequilibrium here is denoted for the CCEMG. Conclusively, for the CCEP it is $\hat{e}_{2i,t-1} = S_{xit} - \hat{\alpha}_x - \hat{\beta}_x Y_{it} - \hat{\eta}_{1xi}\overline{S}_{xit} - \hat{\eta}_{2xi}\overline{Y}_{it}$. For the DCCEMG it becomes $\hat{e}_{2i,t-1} = S_{xit} - \frac{\hat{\alpha}_{xi}}{(1-\hat{\phi}_{AR})} - \frac{\hat{\beta}_{xi}}{(1-\hat{\phi}_{AR})}Y_{it} - \sum_{j=0}^{k}(\frac{\hat{\eta}_{1xik}}{(1-\hat{\phi}_{AR})}\overline{S}_{xit-k} + \frac{\hat{\eta}_{2xik}}{(1-\hat{\phi}_{AR})}\overline{Y}_{it-k})$, where $\hat{\phi}_{AR}$ is the estimated autoregressive coefficient of the lagged dependent variable $S_{xit-1}$.

behaviour of the variables as a response to deviations from the long-run equilibrium. The parameters $\gamma_{xi,t-j}$ and $\nu_{xi,t-j}$ denote the short-run relationships. Cross-sectional averages in first differences are summarized by the vectors $\Gamma_1$ and $\Gamma_2$.[8]

In order to weigh up the goodness of fit against the power of the tests, the numbers of short-run parameters $p_i$ are selected for each country individually. Specifically, I use the Bayesian information criterion to determine the numbers of lags that are included in the test regressions.

The tests for (weak) exogeneity build on the estimates of the country-specific $\lambda$-coefficients $\hat{\lambda}_{1xi}$ or $\hat{\lambda}_{2xi}$. Significant coefficients indicate that the particular variable $S_{xit}$ or $Y_{it}$ adjusts to deviations from the long-run equilibrium and that it is (weakly) endogenous. A significant long-run equilibrium relationship implies that at least one $\lambda$-coefficient is significant (Engle and Granger, 1987). An insignificant $\hat{\lambda}_{2x}$ indicates that the explanatory variable per capita GDP is (weakly) exogenous.

I follow Canning and Pedroni (2008) and choose two test statistics to measure the significance of the $\lambda$-coefficients. The first is the average t-statistic across countries, i.e. $T\text{-}bar = \sum_i t_{\hat{\lambda}i}$. The $T\text{-}bar$ test is assumed to have an $N(0,1)$-distribution. It evaluates whether the hypothesis of (weak) exogeneity should be rejected on average for the panel countries. The second test statistic is a Fisher-type statistic that is computed from the p-values of the country-specific $\lambda$-coefficients. Specifically, it is calculated as $-2\sum_i ln(p_{\hat{\lambda}i})$ and its distribution is $\chi^2(2N)$. The Fisher-statistic evaluates the cumulative significance associated with the country-specific $\lambda$-coefficients. It analyses whether at least some $\lambda$-coefficients are significantly different from zero across countries and, thus, whether we can reject (weak) exogeneity pervasively in the panel.

In addition to the recently described steps of the empirical strategy, several robustness checks are applied to demonstrate the sensitivity of the findings. These concern the role of country outliers, gender-specific differences, and an alternative sample selection. The results of the robustness checks are presented in appendix D.

[8] Thus, $\Gamma_1 = (\Delta\overline{S}_{xt}, \Delta\overline{S}_{xt-1}, ..., \Delta\overline{S}_{xt-l}, \Delta\overline{Y}_{t-1}, ..., \Delta\overline{Y}_{t-l})'$ and $\Gamma_2 = (\Delta\overline{Y}_t, \Delta\overline{S}_{xt-1}, ..., \Delta\overline{S}_{xt-l}, \Delta\overline{S}_{t-1}, ..., \Delta\overline{S}_{t-l})'$.

## 3.2. Data

Two different data sources are used for the analysis in this study. The measures of population health, survival rate and life expectancy estimates, are taken from the Human Mortality Database (2014) (HMD). The HMD offers life table statistics for national populations of 37, mainly European, countries.[9]

As is conventional for empirical works in the field of economic history, data for GDP per capita are taken from the New Maddison Project (2013) database.[10] Data on real per capita GDP is counted in 1990 international Dollars.

As required by the Westerlund (2007) test, country series that contain gaps are excluded from the analysis. In addition, in order to facilitate a credible interpretation of long-run cointegrating relationships, the study only considers countries with numbers of more than 30 available observations. The remaining data set is unbalanced and includes 20 countries[11]. The number of individual periods ranges from 1800-2010 to 1958-2009 and is 113.6 on average. Further information about the sample can be found in Appendix A.

**Table 1:** Descriptive statistics of selected variables and their evolution over time

| Variable | Min | Max | $\Delta_{2008-1800}$ | Avg. $\Delta$ | $\rho_{gdp}$ |
|---|---|---|---|---|---|
| lnGDPpc | 6.641 | 10.363 | 1.800 | 0.019 | 1 |
| SurRate1 | 75.4 | 99.8 | 8.869 | 0.114 | .837 |
| SurRate40 | 26.1 | 98.6 | 23.118 | 0.278 | .860 |
| SurRate80 | 1.4 | 68.4 | 40.094 | 0.394 | .897 |

Notes: Sample contains 20 countries with time periods of 113.6 years on average that range from 1800 to 2008 (2265 observations). $\Delta_{2008-1800}$ is the total change of the variable calculated as $(\sum_i x_{2008} - \sum_i x_{1800})$. Avg. $\Delta$ is the average annual change. $\rho_{gdp}$ is the correlation coefficient of the variable with lnGDPpc.

Table 1 gives a descriptive impression of selected variables and their evolution over time. All variables have increased enormously during the sample period. The table, however, clearly shows that the survival rate 80 has increased most compared to the other survival rates and that its correlation with GDPpc is highest. Thus, from a descriptive point of view the

[9] The HMD data were downloaded in August 2014: http://www.mortality.org

[10] Data used in this analysis were downloaded in January 2015: http://www.ggdc.net/maddison/maddison-project/data.htm. The methodology behind these historical GDP estimates is discussed in Bolt and van Zanden (2014).

[11] These countries are: Australia, Austria, Bulgaria, Canada, Denmark, England Wales Civilian, Finland, France Civilian, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, United States.

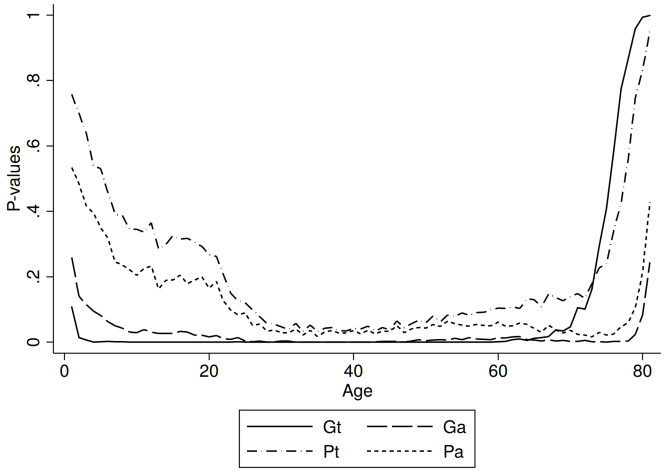
cumulative advantage hypothesis seems to be valid because correlation between per capita income and survival rates increases with age.

# 4. Empirical Results

## 4.1. Tests for Cointegration

Figure 3 depicts the four common-factor-robust p-values obtained by the Westerlund (2007) test. The p-values (y-axis) are plotted against the ages 1 to 80 (x-axis), which denote the particular age-specific survival rate. Thus, the p-values displayed for the age 1 are the cointegration test results for the relationship between per capita GDP and the survival rate of age 1 and so forth.

**Figure 3:** Westerlund 2007 robust p-values for survival rates of ages 1 to 80 as dependent variables




For very young age-groups, the p-values are greater than 0.1 rejecting cointegration between GDP per capita and the survival rate. From that age they steadily decrease during youth and young adulthood and they clearly indicate cointegration for middle adulthood around an age of 40. From an age of around 50, the p-values again increase till they fully reject cointegration at an age of 80. For reasons of clarity, Figure 3 avoids plotting results for ages above 80. These clearly continue to reject cointegration between GDP and survival rates.

The figure also shows that the p-values of the pooled cointegration test statistics are usually greater than the p-values of the grouped statistics. Thus, if we allow for parameter heterogeneity in the estimated relationships across countries, the test statistics are more likely to reject the hypothesis of no error correction. Following Pedroni (1996); Haque et al. (1999);

Eberhardt and Presbitero (2015), this relative performance can be a result of country heterogeneity in the panel.

In addition to Figure 3, Table 2 lists the results for the relationships between per capita GDP and one of three specific survival rates: the survival rates of age 1 and of age 80 for that cointegration with GDP is clearly rejected and for the survival rate of age 40 for that cointegration is definitely maintained. As a complementary finding, the table also documents a significant relationship between per capita GDP and life expectancy at birth, with the latter measuring cumulated survivability across all age-groups.

**Table 2:** Westerlund (2007) test on error correction with measure of population health as dependent and per capita GDP as independent variable

| Statistic | Dependent variable | | | |
|---|---|---|---|---|
| | SurRate1 | SurRate40 | SurRate80 | LifeExp0 |
| *Common factor robust p-value* | | | | |
| Gt | 0.104 | 0.000 | 0.985 | 0.005 |
| Ga | 0.234 | 0.000 | 0.100 | 0.000 |
| Pt | 0.738 | 0.043 | 0.853 | 0.085 |
| Pa | 0.518 | 0.033 | 0.240 | 0.025 |

Notes: Adjustments are made following Persyn and Westerlund (2008): The number of lags and leads are set to 1, the Bartlett Kernel window according to $4(T/100)^{2/9} \approx 4$. Robust p-values are calculated with 800 bootstrap iterations.

## 4.2. Long-Run Coefficient Estimates

Table 3 presents the results of the long-run coefficient estimates that are obtained by the various CCE frameworks. It concerns the survival rate 40 as single dependent variable that proxies mid-age survivability. This approach thus avoid presenting potential spurious regression results for relationships for which cointegration has been rejected (cf. Engle and Granger, 1987). The table also lists the results of the Pesaran (2004) test on cross-sectional dependence that is applied to the estimation residuals.

The first row of Table 3 shows the results of the CCEMG suggested by Pesaran (2006). The CCEMG achieves a positive coefficient of the effect of per capita GDP on the survival rate of age 40 that is significant at the 1%-level. It indicates that a one per cent increase in per capita GDP increases the number of survivors to age 40 by 0.05 out of 100 people.[12] The

[12] The coefficient in table 3 is 5.014. Consider the level-log specification of the estimation equations, the quantitative effect is calculated as $\frac{\beta}{100}\%\Delta GDPpc$.

**Table 3:** Long-run coefficient estimates of per capita GDP on the survival rate of age 40

| Methodology | Coeff. | Std.Error | P-Val. | CD-test | P-Val. |
|---|---|---|---|---|---|
| CCEMG | 5.014 | 1.249 | .002 | -.40 | .692 |
| $\text{CCEMG}_{trend}$ | 3.734 | 1.208 | .000 | .75 | .452 |
| CCEP | 3.782 | .495 | .084 | -.56 | .579 |
| $\text{CCEP}_{trend}$ | 3.665 | 1.935 | .058 | -2.50 | .012 |
| DCCEMG | 4.878 | 1.946 | .012 | -5.96 | .000 |
| $\text{DCCEMG}_{trend}$ | 3.416 | 1.768 | .053 | -3.74 | .000 |

Notes: CCEMG and CCEP proposed by Pesaran (2006), DCCEMG by Chudik and Pesaran (2015). 4 lags of cross-sectional averages are used with the DCCEMG. *trend* denotes the models that are augmented with country-specific linear trend terms. CD-test terms the Pesaran (2004) test statistic that is calculated for the estimation residual and that has a standard normal distribution under the null of cross-sectional independence. Clustered standard errors are reported for the CCEP.

CD-statistic calculated for the estimation residual maintains the null of cross-sectional independence indicating that the CCEMG estimator is not biased by cross-sectional dependence in the variables. Compared to the other estimators, the CD-test statistic for the CCEMG is lowest. Therefore, the CCEMG estimator appears as the preferred estimator with regard to cross-sectional dependence.

Table 3 also presents the results of the alternative CCE frameworks. They all detect significant positive effects of per capita GDP on the survival rate 40 at least at the 10% level. Similar to the results of the Westerlund (2007) test, the p-values associated with the pooled estimation models are higher than the values of the mean-group models that can be a result of potential country heterogeneity.

Figure 4 plots the long-run coefficients and confidence intervals that are obtained by the CCEMG for all survival rates of ages 1 to 100.[13] The figure clearly shows that the life course variations in the relationships between per capita GDP and age-specific survival rates take a hump-shaped form. The effect of per capita income on survivability is small at infant ages; it increases during adolescence, and reaches a maximum during adulthood. Afterwards, it first stagnates, then decreases and diminishes.

### 4.3. Tests for Causality and Weak Exogeneity

Table 4 summarizes the results of the exogeneity tests that are depicted by Equations 4 and 5. The tests are carried out for those particular relationships for which cointegration has been detected; these are represented by the relationship between per capita GDP and the survival

[13] Similar graphs for the other CCE estimators can be found in the appendix.

**Figure 4:** CCEMG-coefficients for survival rates 1 to 100 as dependent variables


rate of age 40. The tests concern all the long-run coefficient estimates that are obtained by the various CCE frameworks.

**Table 4:** Tests for (weak) exogeneity between per capita GDP and the survival rate of age 40

| Framework | Variable | Avg. $\lambda$ | *T-bar* | P-Val. | Fisher | P-Val. |
|---|---|---|---|---|---|---|
| CCEMG | SurRate40 | -0.200 | -2.802 | 0.005 | 255.964 | 0.000 |
| | lnGDPpc | 0.009 | 0.926 | 0.354 | 94.808 | 0.000 |
| CCEMG$_{trend}$ | SurRate40 | -0.293 | -3.501 | 0.000 | 363.313 | 0.000 |
| | lnGDPpc | 0.010 | 0.635 | 0.525 | 87.417 | 0.000 |
| CCEP | SurRate40 | -0.182 | -2.735 | 0.006 | 259.146 | 0.000 |
| | lnGDPpc | 0.008 | 0.702 | 0.483 | 70.696 | 0.002 |
| CCEP$_{trend}$ | SurRate40 | -0.265 | -3.394 | 0.001 | 346.304 | 0.000 |
| | lnGDPpc | 0.011 | 0.731 | 0.465 | 85.341 | 0.000 |
| DCCEMG | SurRate40 | -0.196 | -2.813 | 0.005 | 317.580 | 0.000 |
| | lnGDPpc | 0.000 | -0.082 | 0.935 | 28.568 | 0.911 |
| DCCEMG$_{trend}$ | SurRate40 | -0.303 | -4.148 | 0.000 | 433.464 | 0.000 |
| | lnGDPpc | -0.001 | -0.212 | 0.832 | 29.176 | 0.897 |

Notes: Framework denotes the particular CCE framework by which the long-run coefficients are obtained. *T-bar* is the average t-statistic of the $\hat{\lambda}_i$ coefficient across countries that is distributed $N(0,1)$. Fisher gives -2$\sum_i ln(p_{\hat{\lambda}i})$, which has a distribution of $\chi^2(2N)$. The lag order of short-run dynamics is selected country-specifically by the Bayesian information criterion with numbers of lags ranging between 1 and 3. The number of cross-sectional averages in first differences is fixed at 3. Null hypothesis is (weak) exogeneity of the corresponding variable.

We first consider the test results for the dependent variable that build on the coefficients $\lambda_{1i}$ in Equation 4. Both the average t-statistic *T-bar* as well as the Fisher statistic are clearly significant for all estimation frameworks. Thus, the tests reject exogeneity of per capita GDP

and confirm causality running from per capita GDP to the survival rate of age 40 both on average and pervasively in the panel.

The results for the dependent variable GDP per capita that build on the coefficients $\lambda_{2i}$ in Equation 5 give a mixed picture. Taking a look at the results for the static estimators, the CCEMG and CCEP, the Fisher statistic is significant showing that there is reverse causality from the survival rate to per capita GDP at least in some sample countries. However, the *T-bar* statistic is insignificant, thus rejecting reverse causality on average across countries. Consequentially, the coefficient estimates of the static estimators seem to be biased by reverse causality only in some countries and a potential coefficient bias due to reverse causality can be rejected on average across countries.

Nevertheless, the results of the dynamic CCE estimator (DCCEMG) stand out. Both the average t-statistic and the Fisher test are insignificant confirming weak exogeneity and rejecting a potential coefficient bias due to reverse causality even pervasively in the panel. This finding agrees with Chudik et al. (2015), who claim that a dynamic autoregressive specification of the CCE estimator can be robust to simultaneity bias.

Summarizing the results of the exogeneity tests, we can see that causality in the present panel runs from per capita GDP to the survival rate of age 40 on average across countries but runs in the opposite direction only in some sample countries. The assumptions of weakly exogenous regressors can be maintained on average across countries for all estimation frameworks and even pervasively in the panel for the dynamic CCE estimator.

## 5. Summary and Discussion

Motivated by the empirical literature on life course epidemiology, this study asks whether increases in per capita income provoke advantages in population health and whether these advantages differ across population age-groups. Finding an answer to this question is relevant because the related literature remains quite inconclusive and provides contrary evidence in favour of one of two hypotheses, the *cumulative advantage* or the *age as leveller* hypothesis. In addition, a life course perspective on the income-to-health relationship has been concerned in micro-level studies and these studies may estimate a relative income effect rather than an effect of absolute income. On these grounds, the present analysis is an attempt to transfer

the investigation to an aggregate level and to support one of the two hypotheses with macro-empirical evidence.

The crucial result of this study is that the relationship between per capita income and survivability takes a hump-shaped form across ages. Per capita income has a positive significant effect only on survival rates of middle age-groups. It has no significant effect on survival rates at both very young and old ages. Thus, it appears that factors other than income must account for the comparatively great evolution of survival rates of old ages that can be observed in the present data.

Interpreting the results shows that evidence is detected for both hypotheses during several stages of the life course. While the *cumulative advantage* mechanism seems to be valid for the years of life till late adulthood, the *age as leveller* hypothesis corresponds to the years of life afterwards. A secondary but insignificant result is that the *cumulative advantage* mechanism is stronger but is predominated by the *age as leveller* mechanism at an earlier stage for males than for females.

The basic results confirm the findings of some micro-level investigations claiming that socio-economic conditions are of particular relevance for health during middle ages (see Mishra et al., 2004; House et al., 1994).

Prima facie, the results of this study contradict Goldstein (1985) and Pritchett and Summers (1996), who find a significant effect of per capita GDP on infant survivability. However, these studies include many developing economies in their analysis. Goldstein (1985) emphasizes the relevance of basic human needs in determining infant survivability. As the present study tends to focus more on developed economies, these basic human needs might already been achieved in most sample countries even at the beginning of the sample period.

The findings of this study have important policy implications. Policy makers should take the age-specific differences in the income-to-health relationship into account when balancing costs and quality of policy interventions. Modern societies have already invested much in public health care and pension systems during the last few decades. Therefore, it seems that the very young and the elderly are largely insensitive to increases in per capita income. In contrast, middle age-groups seems to be affected by changes in per capita GDP. Thus, the challenge for policy makers is to establish well-customized prevention schemes for these middle age-groups. Specifically, the goal is to reduce their economic risks and their specific probability to be affected by economic downturns.

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# Appendix

## A. Sample Details and Descriptive Statistics

**Table A1:** Data coverage per sample country

| Country | Coverage | # of Observations |
|---|---|---|
| Australia | 1921–2009 | 89 |
| Austria | 1947–2010 | 64 |
| Bulgaria | 1950–2010 | 64 |
| Canada | 1921–2009 | 89 |
| Denmark | 1835–2010 | 176 |
| England-Wales-Civilian | 1841–2010 | 170 |
| Finland | 1878–2009 | 132 |
| France-Civilian | 1820–2010 | 195 |
| Hungary | 1950–2009 | 60 |
| Ireland | 1950–2009 | 60 |
| Italy | 1972–2009 | 138 |
| Netherlands | 1850–2009 | 160 |
| New-Zealand | 1948–2008 | 61 |
| Norway | 1846–2009 | 164 |
| Poland | 1958–2009 | 52 |
| Portugal | 1940–2010 | 71 |
| Spain | 1908–2010 | 103 |
| Sweden | 1800–2010 | 211 |
| Switzerland | 1876–2010 | 135 |
| United-States | 1933–2010 | 78 |

**Table A2:** Summary statistics

| Variable | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| lnGDPpc | 8.641 | 0.904 | 6.641 | 10.363 |
| SurRate1 | 93.552 | 6.187 | 75.399 | 99.758 |
| SurRate40 | 82.143 | 16.240 | 26.122 | 98.553 |
| SurRate80 | 29.754 | 16.165 | 1.378 | 68.400 |

**Figure A2:** Log of GDP per capita by country over period 1800-2010

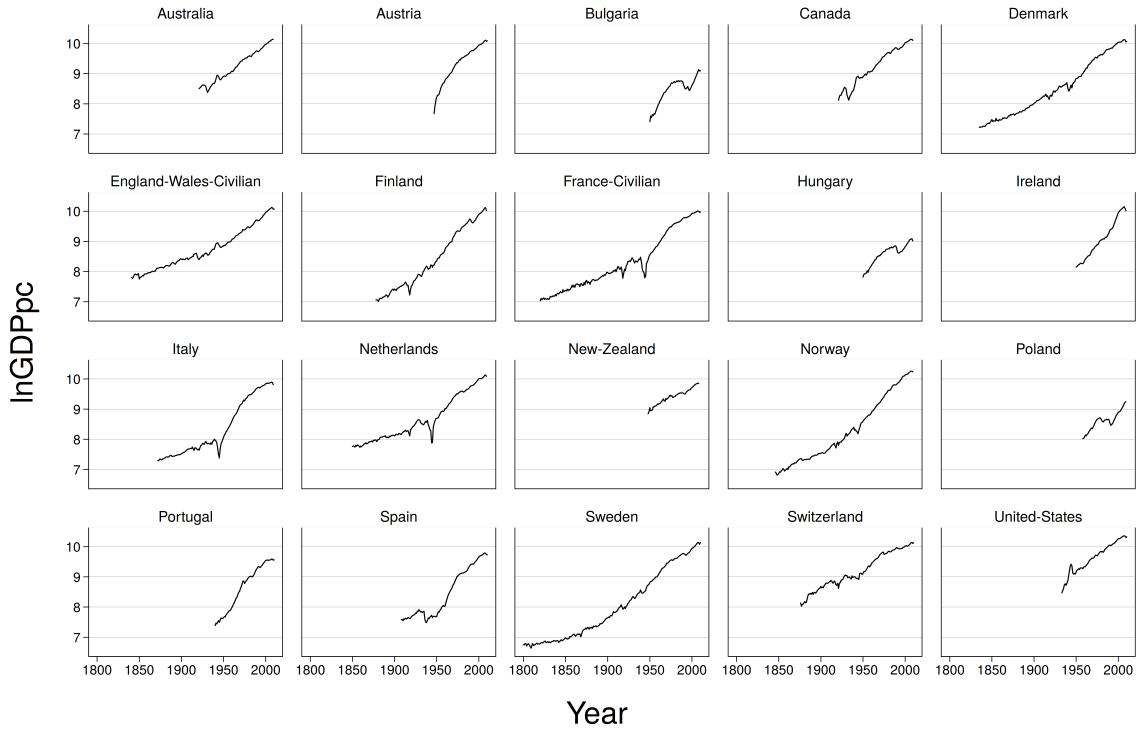



**Figure A2:** Survival rate of age 1 by country over period 1800-2010

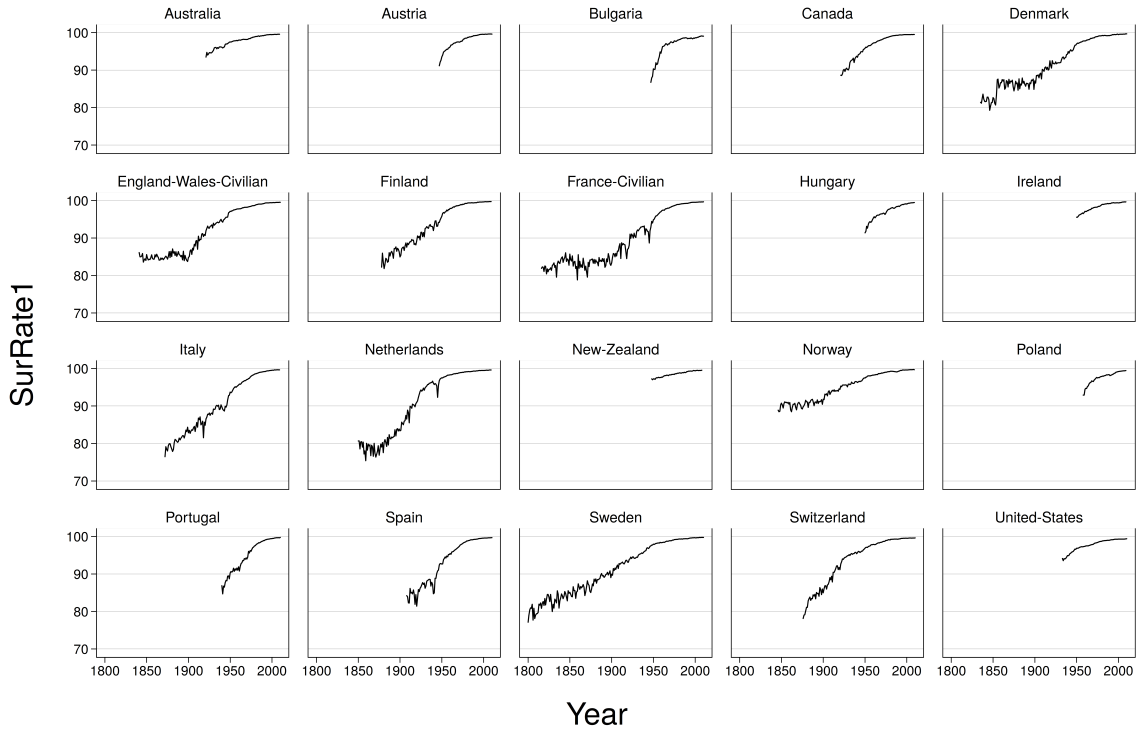


**Figure A2:** Survival rate of age 40 by country over period 1800-2010

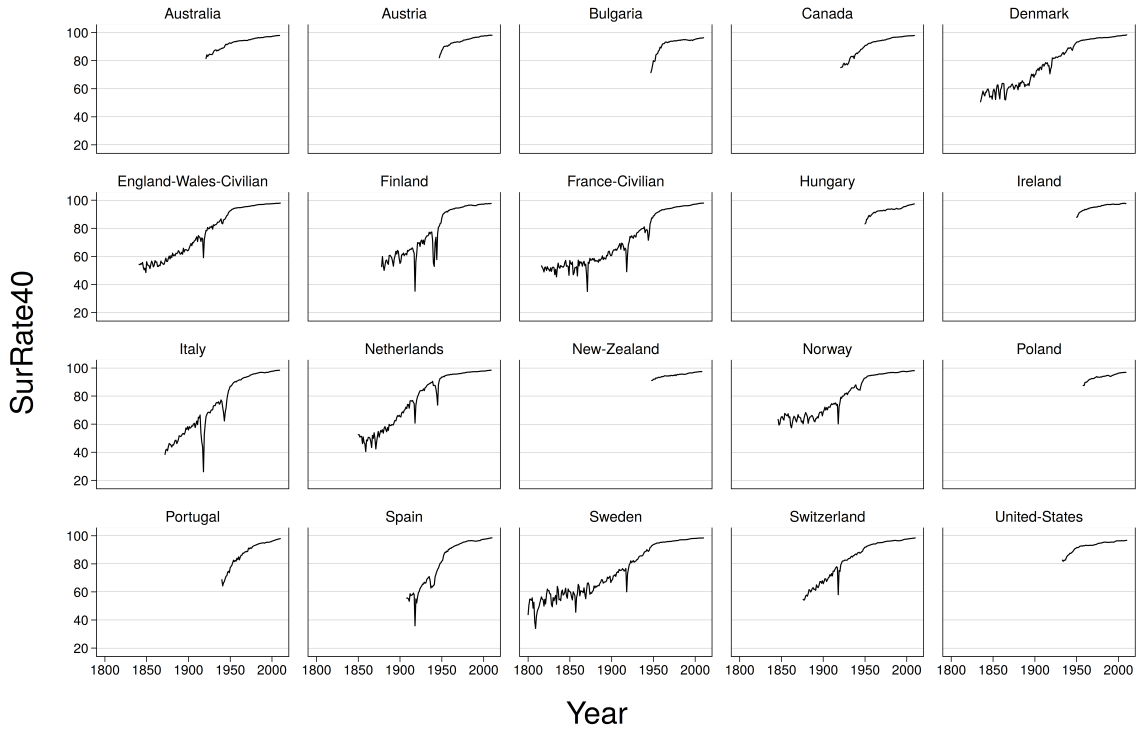
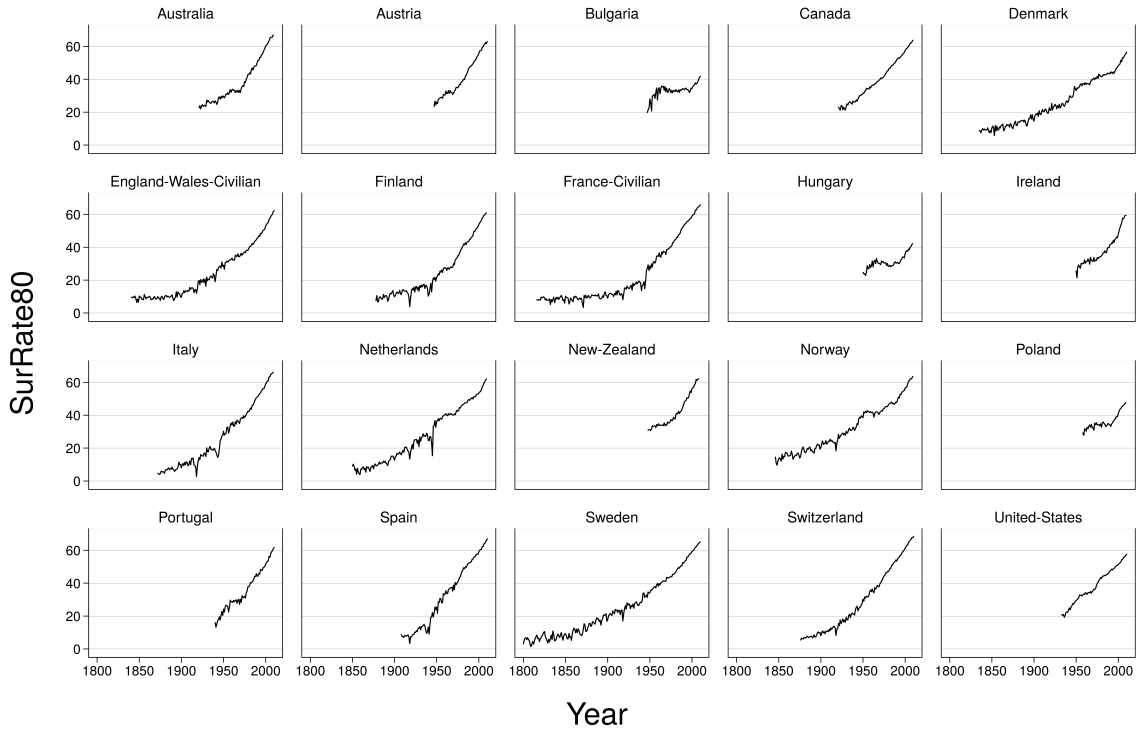



**Figure A2:** Survival rate of age 80 by country over period 1800-2010



## B. Test on Cross-Section Dependence

Evidence for existing cross-section dependence in the variables is provided by the results of the Pesaran (2004) test. The test, first, calculates the correlation coefficients $\hat{\rho}_{ij}$ for each correlation between the variable of country $i$ with country $j$. The test statistic is, then, computed as

$$CD = \sqrt{\frac{2}{(N(N-1))}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}\hat{\rho}_{ij}}\right) \quad , \tag{6}$$

where $T_{ij}$ is the number of observations the variable is available for both countries. The test results for emphasized variables are presented in table A3. They all reject the hypothesis of cross-section independence.

**Table A3:** Pesaran (2004) CD-test

| Variable | CD-test | p-value | $\rho_{ij}$ | abs($\rho_{ij}$) |
|---|---|---|---|---|
| | | *Levels* | | |
| lnGDPpc | 118.92 | 0.000 | 0.960 | 0.960 |
| SurRate 1 | 119.44 | 0.000 | 0.967 | 0.967 |
| SurRate40 | 118.84 | 0.000 | 0.959 | 0.959 |
| SurRate80 | 114.58 | 0.000 | 0.926 | 0.926 |

Notes: $\rho_{ij}$ denotes the average correlation coefficient and *abs($\rho_{ij}$)* the absolute average correlation coefficient. CD-test statistic is distributed standard normal. The null hypothesis is cross-section independence.

## C. Unit Root Tests

The cointegration analysis applied in this study relies on the assumption of non-stationary variables that are integrated at order one, i.e. $I(1)$.

In order to test the validity of this assumption, table A4 presents the results of the Pesaran, Smith and Yamagata (2013) panel unit root test (CIPSM) for all emphasized variables. The CIPSM-test allows to capture multiple unobserved common factors by augmenting the individual Dickey-Fuller equations with lagged cross-section averages and their lagged differences of both, the variable of interest $y$ and an additional regressors $z_j$. The Dickey-Fuller equations thus are

$$\begin{aligned}\Delta y_{it} = \phi_{i0} + \phi_i^y y_{i,t-1} + \sum_{l=0}^{p} \gamma_{i,t-l}^y \Delta y_{i,t-l} + \phi_i^{\overline{y}} \overline{y}_{i,t-1} + \sum_{l=1}^{p} \gamma_{i,t-0}^{\overline{y}} \overline{\Delta y_{i,t-l}} \\ + \sum_{j=0}^{k} \phi_{j,i}^{\overline{z}} \overline{z_{j,i,t-1}} + \sum_{j=0}^{k} \sum_{l=0}^{p} \gamma_{j,i,t-l}^{\overline{z}} \overline{\Delta z_{j,i,t-l}} \quad ,\end{aligned} \tag{7}$$

where $k$ is the number of additional regressors $z$ and $y$ is one of the variable used in this analysis.

The results presented in table A4 show that for the variables in levels, the null hypothesis of non-stationarity can not be rejected; it is rejected for the variables in first differences. Thus, all the selected variables are integrated at order one, I(1).

**Table A4:** Pesaran, Smith, and Yamagata 2013 panel unit root test (CIPSM)

| *deterministics* : *constant* + *trend* | | | | | | |
|---|---|---|---|---|---|---|
| Variable | lnGDPpc | SurRate1 | SurRate40 | SurRate80 | Crit. Values 1% | 5% |
| | | | $k = 1$ | | | |
| $Z_1$ | LifeExp0 | lnGDPpc | lnGDPpc | lnGDPpc | | |
| *Stat* | -2.107 | -2.188 | -2.207 | -1.912 | -2.96 | -2.79 |
| | | | $k = 2$ | | | |
| $Z_1$ | LifeExp0 | lnGDPpc | lnGDPpc | lnGDPpc | | |
| $Z_2$ | SurRate1 | LifeExp0 | LifeExp0 | LifeExp0 | | |
| *Stat* | -2.135 | -2.340 | -2.514 | -1.884 | -3.10 | -2.91 |

| *deterministics* : *constant* | | | | | | |
|---|---|---|---|---|---|---|
| Variable | lnGDPpc | SurRate1 | SurRate40 | SurRate80 | Crit. Values 1% | 5% |
| | | | $k = 1$ | | | |
| $Z_1$ | LifeExp0 | lnGDPpc | lnGDPpc | lnGDPpc | | |
| *Stat* | -1.489 | -1.963 | -1.598 | -1.465 | -2.54 | -2.36 |
| | | | $k = 2$ | | | |
| $Z_1$ | LifeExp0 | lnGDPpc | lnGDPpc | lnGDPpc | | |
| $Z_2$ | SurRate1 | LifeExp0 | LifeExp0 | LifeExp0 | | |
| *Stat* | -1.301 | -1.750 | -2.011 | -1.404 | -2.71 | -2.53 |

| *deterministics* : *constant* | | | | | | |
|---|---|---|---|---|---|---|
| Variable | $\Delta$.lnGDPpc | $\Delta$.SurRate1 | $\Delta$.SurRate40 | $\Delta$.SurRate80 | Crit. Values 1% | 5% |
| | | | $k = 1$ | | | |
| $Z_1$ | $\Delta$.LifeExp0 | $\Delta$.lnGDPpc | $\Delta$.lnGDPpc | $\Delta$.lnGDPpc | | |
| *Stat* | -3.613 | -4.041 | -4.336 | -4.119 | -2.54 | -2.36 |
| | | | $k = 2$ | | | |
| $Z_1$ | $\Delta$.LifeExp0 | $\Delta$.lnGDPpc | $\Delta$.lnGDPpc | $\Delta$.lnGDPpc | | |
| $Z_2$ | $\Delta$.SurRate1 | $\Delta$.LifeExp0 | $\Delta$.LifeExp0 | $\Delta$.LifeExp0 | | |
| *Stat* | -3.398 | -4.113 | -4.265 | -3.905 | -2.71 | -2.53 |

Notes: $k$ indicates the number of additional regressors. $Z_1$ and $Z_2$ indicate the variables that enter the regressions as additional cross-section averages. The number of lagged first differences included in the Dickey-Fuller regressions is set fixed to 6 for all countries. Following Pesaran et al. (2013), the test statistic is calculated as averaged t-statistic across $N$ countries. The null hypothesis is non-stationarity in all individual variable series, the alternative hypothesis is (trend) stationarity in the variable series in at least one country.

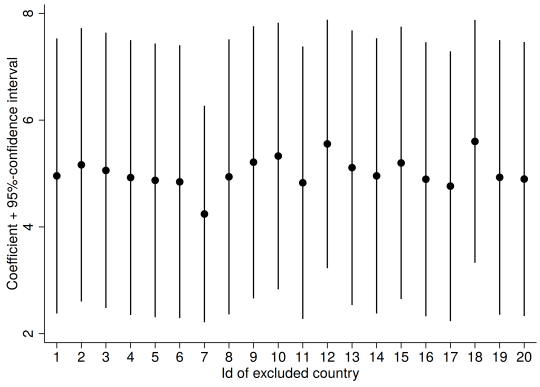
# D. Robustness Tests and Extensions

The robustness of the main findings that are obtained in this study demonstrated in several sensitivity test. These test are described and their results are presented in the following subsections.

## D.1. Country Outliers

In order to test whether the main results are robust to country outliers, the CCEMG is re-estimated by successively excluding one country at a time from the sample. Figure A4 plots the 20 coefficient estimates for the survival rate of age 40 as dependent variable; the x-axis indicates the id of the excluded country. It shows that the coefficient estimates as well as their significance remain quite stable indicating that the coefficient estimates are not driven by individual outliers.

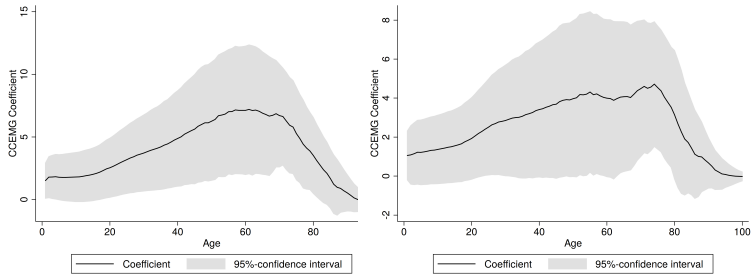
**Figure A4:** CCCEMG coefficient estimates and their robustness to country outliers




## D.2. Modification in the Estimation Framework

Several modifications of the estimation framework have already been concerned in the previous analysis: the augmentation with a country-specific linear trend term, a pooled estimation instead of the mean-group estimation procedure, and a dynamic representation with lagged dependent variables as suggested by Chudik and Pesaran (2015). The following graphs plot the long-run coefficients of these alternative framework and, thus, document that the result of an inverse U-shaped form across the age-specific relationships hold.


**(a)** CCEMG$_{trend}$ **(b)** CCEP **(c)** CCEP$_{trend}$




**(d)** DCCEMG **(e)** DCCEMG$_{trend}$

**Figure A4:** Coefficient of CCE estimation variants across age-groups

## D.3. Conditional Survival Rates

The previous analysis relies on unconditional survival rate estimates that capture mortality from birth to a particular age. These are directly available from the data sources. In contrast, conditional survival rates capture survivability between two particular ages and have to be calculated ex-post on the basis of a-priori assumptions on the age-intervals. This section shows that the findings are robust to the use of conditional survival rates instead of unconditional ones.

Table A5 contains the Westerlund (2007) test results for the relationships between per capita GDP and the survival rate of age 50 conditional on reaching the age 1 as well as the survival rate of age 80 conditional on reaching the age 50. They show that while survivability between the ages 1 and 50 forms a significant cointegrating relationship with per capita GDP, survivability between the ages 50 and 80 does not.

**Table A5:** Westerlund (2007) test with conditional survival rates as explanatory variables

| Statistic | Dependent variable | |
|---|---|---|
| | CondSurRate1-50 | CondSurRate50-80 |
| *Common factor robust p-value* | | |
| Gt | 0.000 | 0.999 |
| Ga | 0.006 | 0.190 |
| Pt | 0.011 | 0.589 |
| Pa | 0.015 | 0.116 |

Notes: Adjustments are made following Persyn and Westerlund (2008): The Bartlett Kernel window according is set to $4(T/100)^{2/9} \approx 4$. The number of lags and leads are set to 1-2 and 1 respectively. Robust p-values are calculated with 800 bootstrap iterations.

## D.4. Gender Differences

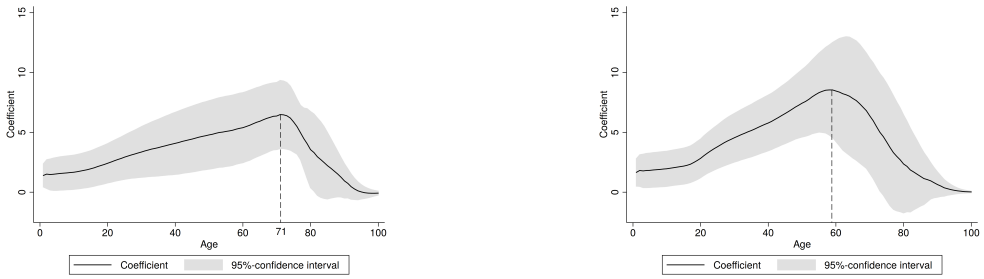
It is generally accepted that females live, on average, longer than males. Calculated as sample mean, life expectancy is 4.68 years higher for females than for males in the present data.

The analysis of life course variations in the income-to-health relationship that is conducted in this study exploits survival rates calculated for both females and males together and, thus, does not consider gender differences. However, it is worth to know whether the results of this study are robust to gender-specific differences.

Survival rate estimates separated for both females and males are available from the human mortality database. The figures A5 plot the age-specific long-run coefficients of the CCEMG

estimator separated for both sexes females and males. An inverse U-shaped relationship can be read from both figures showing that the main result of this study is robust to gender-specific differences. The age-specific coefficients do not differ significantly between females and males but they slightly indicate that both the *cumulative advantage* and the *age as leveller* mechanism appear differently during the gender-specific life courses.

For females the accumulation of health related benefits from economic growth is smoother but continues until higher ages. For males, the *cumulative advantage* mechanism is stronger but is countervailed and predominated by the *age as leveller* mechanism much earlier in live than for females. More precisely, the coefficient of the effect of per capita income on survivability takes its highest value at age 71 for females but at age 59 for males. Thus, males depend more on the health related benefits from economic growth during middle ages but their cumulative advantages start to diminish 12 years earlier compared to females.




**(a)** Females **(b)** Males

**Figure A5:** Gender-differences in coefficients across age-groups

## D.5. Extension of the Data Sample

The dynamic and cointegation approach that has been applied in this study requires long and continuous time series. Therefore, several country-specific data have been excluded from the analysis because they contain gaps or they have very few observations. Table A6 lists the 12 previously excluded countries and gives information about the particular data coverage.

This section shall demonstrate that the inclusion of the 12 additional countries does not change the main findings of this study. Specifically, it is analysed whether the results of the CCE mean-group estimator of Pesaran (2006) hold in an extended panel of altogether 32 countries. The extended panel is composed of both the 20 countries that have already been concerned in the previous analysis and the 12 additional countries listed in table A6. The

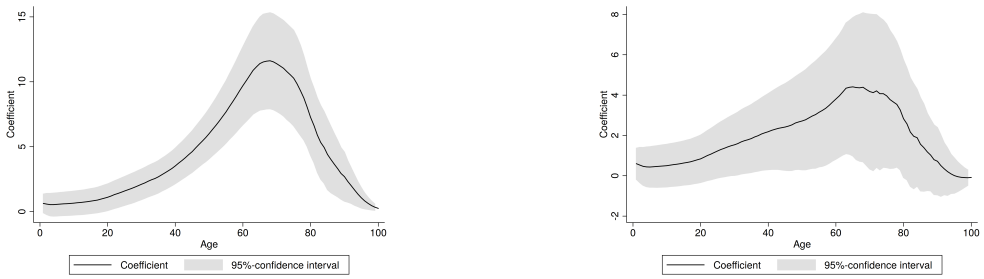
**Table A6:** Data coverage in additional countries

| Country | Coverage | Gap | # of Observations |
|---|---|---|---|
| Belarus | 1973–2010 | 1974–1989 a | 22 |
| Belgium | 1846–2010 | 1914–1918 b | 160 |
| Chile | 1992–2008 | – | 17 |
| Czech-Republic | 1990–2010 | – | 21 |
| Estonia | 1973–2010 | 1974–1989 a | 22 |
| Germany | 1990–2010 | – | 21 |
| Latvia | 1973–2010 | 1974–1989 a | 22 |
| Lithuania | 1973–2010 | 1974–1989 a | 22 |
| Russia | 1973–2010 | 1974–1989 a | 22 |
| Slovakia | 1990–2009 | – | 20 |
| Slovenia | 1983–2009 | – | 27 |
| Ukraine | 1973–2010 | 1974–1989 a | 21 |

Notes: a / b denotes that the gap is due to missing data in the Human Mortality data base or the Maddison Project database respectively.

CCE mean-group estimator is advantageous at this point because it is a static approach that can be a applied to fragmentary time-series without difficulties.

Figures A6 plot the coefficient estimates and their 95% confidence intervals across age-groups for both cases without and with a country-specific linear trend term. The plotted coefficients clearly take a hump-shaped form. In that way, they document the robustness of the findings to an extension of the panel.




**(a)** Without trend **(b)** With trend

**Figure A6:** CCE mean-group estimates for an extended panel of 32 countries

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