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

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Korbinian Nagel [‡]

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. Since related micro level studies are criticised due to an income-rank effect, this study transfers the investigation of both hypotheses to a macro level with a long time horizon. It asks whether increases in per capita income improve population health and whether the improvements differ across population age groups. The analysis uses an unbalanced panel data set with 20 countries and up to 211 years, and relies on an error correction and common factor framework to investigate the long-run equilibrium relationship between income and selected measures of age specific population health. A significant effect of per capita income on survival rates is found for middle ages but not for very young and for old ages. From this it can be concluded that while the *cumulative advantage* theory describes the transition from young to middle ages, the transition from middle to old ages corresponds to the *age as leveller* mechanism.

JEL classification: J11; C22; I15;

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

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1. Introduction

Within the literature on life course epidemiology, many studies investigate whether the importance of income as health determinant varies during the years of life. These studies have established two contrary hypotheses on how the income-to-health 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 clear 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 the income is available. Consequentially, the effects of income on health should be stronger at older ages 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 during the life course and that income is a less decisive determinant for health at higher ages (see e.g. House et al., 1994; Beckett, 2000; Mishra et al., 2004).

Life course variations in the income-to-health relationship are investigated in many survey studies that use individual level data. The results of these studies are object of many critiques, because they do not estimate an equilibrium relationship (cf. Acemoglu and Johnson, 2007) and they do not address the importance of the relative economic position within the society (cf. Marmot and Nazroo, 2001; McMunn et al., 2006). People that are in better economic positions compared to other society members may have access to exclusive medical resources; to put it differently, the most competent doctors may medicate only the richest. Individual level studies, therefore, may capture rather the selection of the available medical resources toward better endowed society members. Further, several studies stress the perception of place in the social hierarchy and argue that, due to psychosocial factors, the income rank is the important health determinant and not income itself (see e.g. Lynch et al., 2000).

This critique of the income rank is justified only at the micro-level. An analysis that is beyond these objections is possible at an aggregate level by investigating the population as a whole. To my knowledge, however, the macro-empirical literature still misses the life course analysis of the income-to-health relationship. To narrow this gap, and to test the *cumulative advantage* versus

the *age as lever hypothesis*, this study conducts a cross age comparison of survival conditions at a country level.

Related macro-empirical studies commonly focus on one or two measures of population health, mostly life expectancy at birth or infant mortality. Their aim is to investigate a representative and meaningful health indicator that is statistically reliable, in particular for developing economies (see Goldstein, 1985; Pritchett and Summers, 1996). However, data on mortality that can be linked to its 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 population life course. The present study takes advantage of the age dimension in the available data and estimates the effect of per capita income on a set of survivability indicators that correspond to different ages. In particular, survival rates at age 1, 50, and 80 are selected in order to illustrate representative stages of life.

The focus on developed economies has another advantage. 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. It contains a high number of periods reaching from 52 to 211 years per country but covers only 20 countries because the availability of detailed data is limited. The long data availability allows one to empirically link long-term economic and health transitions and to involve a time series perspective in order to draw conclusions on causality.

Regarding the econometric strategy, this study addresses several methodological weaknesses that are present in the existing macroeconomic literature. Studies either conduct cross country panel data analyses that neglect cross country heterogeneity in the income-to-health relationship (see e.g. Goldstein, 1985; Pritchett and Summers, 1996), or they apply individual time series methods that address cross country heterogeneity but do not account for the presence of common factors (see e.g. Swift, 2011). Common factors can be seen as deterministic driver of population health as well of per capita income. They reflect common shocks such as the impacts of global technological progresses. Using panel time series methods, the empirical setting of this study captures heterogeneous common factor impacts, and it also allows for cross country heterogeneity in the estimated relationship.

The empirical investigation finds that increases in per capita income affect life expectancy at birth as well as the survival rate at age 50. In contrast, it can not identify a significant effect on the infant survival rate as well as the survival rate at age 80. Consequentially, evidence for

the *cumulative advantage hypothesis* is found only for the transition from young to middle ages, whereas the transition from middle to old ages corresponds to the *age as leveller* mechanism.

The study is closely linked to two bodies of empirical analyses. As pointed out above, the first contain survey studies that investigate the relationship between socio-economic resources and health under a life course perspective. These studies controversially discuss empirical evidence for both hypotheses (see Ross and Wu, 1996; Beckett, 2000; Mishra et al., 2004; Dupre, 2007; Willson et al., 2007). One study, House et al. (1994) is of particular interest here as it provides quite similar results compared to the findings of this study. It analyses the separate effects of education and income on health and finds evidence for an increasing effect during adulthood until relatively late in life, when the health differences provoked by income and education diminish. Thus, the authors find that the *cumulative advantage* theory describes the income-to-health relationship during young and middle adulthood, whereas the *age as leveller* mechanism corresponds to senior ages.

The second body of literature that is closely related to this study is the macro-empirical literature that estimates the effect of per capita income on population health. Specifically one study again has much in common with the present analysis because it uses quite similar data sources and a related econometric methodology: Swift (2011) considers 13 OECD countries for periods ranging from 1820–2001 to 1920–2001. Applying individual vector error correction models, it finds positive effects of GDP per capita on life expectancy for most but not all countries in the sample. However, Swift (2011) focuses on life expectancy as single and comprehensive health indicator and, in contrast to the present analysis, it does not concern age differences in population health in order to involve a life course perspective.

The present study is organized as follows. Section 2 motivates the analysis and provides a theoretical and descriptive background. Section 3 presents the empirical strategy and describes the data. Section 4 presents the results. Section 5 summarizes and concludes.

2. Motivating Background

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

The literature on life course epidemiology explores the temporal ordering of health related factors and their subsequent health outcomes (Kuh et al., 2003). Someone's health status does not only depend on his actual life style but on his earlier life or even on the life of his parents (cf. Smith

et al., 2000). The economic and social conditions in which a person is born, grows up, and spends adulthood are decisive determinants of it's health when the person is ageing.

The life course perspective gives rise to the concept of an accumulation mechanism and thus, to the *cumulative advantage* hypothesis. The impacts of favourable and unfavourable health conditions strengthen themselves when they are experienced continuously or during several moments in life. Brunner et al. (1999), in a survey study, show that the accumulation of cardiovascular risks begins in childhood and continues in adulthood. Power and Hertzman (1997) argue that adult disease can be understood mostly when the effects of social and biological risks occurring at different stages of life are jointly taken into account. Hertzman et al. (2001) include quite a number of social and economic health determinants of earlier and contemporary life in an integrated econometric model. Observing the 1958 British Birth Cohort, they find that the effects of childhood and contemporary factors do not offset each other and that all factors together explain self related adult health mostly.

Specifically concerning the impacts of income and education, Ross and Wu (1996) analyse 2,031 respondents of an U.S telephone interview survey and find that the health disparities created by education and income diverge with age. Similar evidence is provided by Willson et al. (2007). According to their empirical investigation, the exposure to advantages and disadvantages across a particular duration of time produces health disparities and the returns to socio-economic resources increase with age.

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 mechanism that is mentioned as the *age as leveller* hypothesis (cf. Beckett, 2000; Dupre, 2007). Observing the Australian Longitudinal Study on Woman's Health, Mishra et al. (2004) claim that health differentials across tertiles of socio-economic status were more evident for the mid-age cohort than for the older cohort. Jatrana and Chan (2007) show that among Singaporean adults health inequalities related to the socio-economic status decline slightly but do not disappear with higher ages. Woo et al. (2000) find that absolute income is not an important factor contributing to mortality and morbidity of the elderly population in Hong Kong aged 70 years and above.

While the *cumulative advantage* hypothesis has a clear theoretical foundation due to the accumulation of health related factors, the *age as leveller* mechanism lacks such a clear explanation.

The literature specifies only few mechanisms that are capable to explain the levelling phenomenon at a macro level and for a relatively long time horizon.

One argument is public old-age care. Modern societies have invested much in public health care and pension systems. These welfare policies surely have reduced poverty and hindrance to health care among the elderly and therefore may have lowered the importance of income increases for old ages compared to middle ages (cf. Preston, 1984; House et al., 1994).

Selective mortality is a further and prominent explanation for the levelling phenomenon that is discussed controversially in the related literature (see Beckett, 2000; Dupre, 2007; Rohwer, 2016). Typical frail members of the population for that income is a decisive health factor may die relatively early. The surviving members may be less sensitive to income gains and losses.

Furthermore, a specific and small bulk of literature also suggests that income is not a decisive determinant of health in very high ages. Investigations concerning the Okinawa cluster of centenarians (e.g. Willcox et al., 2007), for example, stress that typical determinants of longevity and healthy ageing are long-term caloric restrictions, temporary negative energy balances at younger ages, and an active but stress-less life style. Such factors are suspected to have an ambiguous link to income, providing evidence that income may be an important determinant for extreme longevity.

2.2. The Life Course Framework from a Macroeconomic Perspective

Consider that both hypotheses are developed and discussed in micro-level studies and take into account that these studies may not be able to distinguish the pure income effect from the income rank effect. It remains a question of interest whether we can observe similar life course pattern in the income-to-health relationship at the country level.

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, anyhow through increasing consumption possibilities, through improving the provision of health care goods, or through reducing the exposure risk to episodes of economic scarcity.

According to the *cumulative advantage* hypothesis, older age groups should have had more opportunities to collect the advantages of per capita income during their relative long lives. Consider, for example, that an increase in per capita income has rendered a specific medical treatment that raises the probability to survive. The probability that this treatment is demanded

by a specific society member increases with its age and, implying that the health effect of per capita income is stronger for older age groups.

Figure 1: Understanding the impacts of economic growth on health in a life course perspective

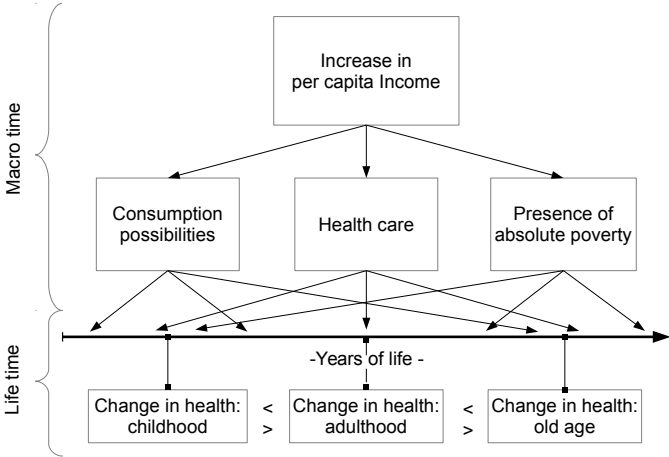
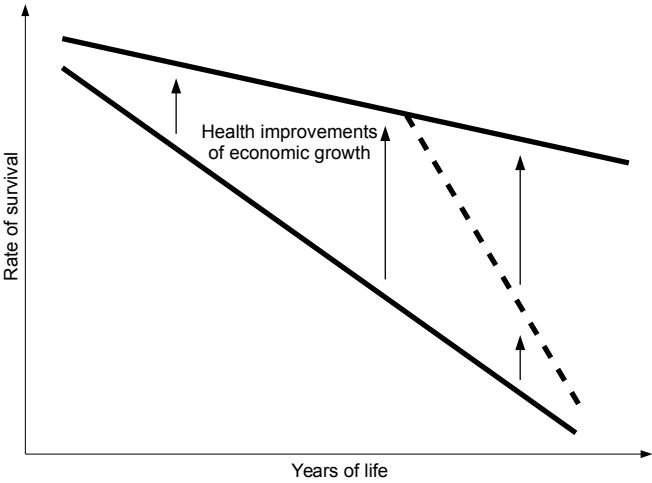


Figure 1 illustrates the life course impacts of per capita income. It incorporates two time dimensions (cf. Elder, 1975). First, a *macroeconomic time* at which improvements in health conditions are rendered by increases in per capita income. Second, the *life time* of individuals and their age groups during that the transmissions of health factors from the general macroeconomic evolution occur. These transmissions lead to changes in health outcomes that can be observed at various stages of life.

Figure 2: Survival rates and economic growth in a life course perspective



The potential results of these mechanisms is also sketched in figure 2. The plotted lines depict stylized survival rates as a declining function of age. While the lower continuous line indicates survivability before a boost in per capita income occurs, the upper continuous line does the same for survivability after the boost and under the assumption of an accumulation mechanism. The dashed line incorporates the potential impact of *age as leveller* during higher ages as it is described by House et al. (1994). In that view, accumulation is observable up to middle and younger-old ages and from that point age reduces the advantages generated by an income increase.

2.3. Age specific Population Health

The hypothesised age differences in the macroeconomic income-to-health relationship can be investigated, if the available data allows an age group differentiation of health conditions. This study focuses on survival rate estimates that can be calculated from death counts and for any particular population age group. Survival rates facilitate the comparison of survival and health conditions across all ages. They specify the number of people out of total population that survive to any particular age x , or, to put it differently, to their x th birthday. From a life course perspective they proxy the health conditions to that a representative member of the population is exposed from his birth to the age x .

Specifically, the present analysis focuses on three measures of population health that should illustrate survival conditions of three stages of life. The survival rate of age one stands for very young ages, the survival rate of age 50 for middle and working ages, and the survival rate of age 80 proxies health and survivability of old ages. In addition, life expectancy at birth is included as comprehensive indicator reflecting all age groups simultaneously.

Table 1: Selected variables and their evolution over time

Variable	Min	Max	Total sample growth	Average sample growth rate	Correlation with GDPpc
GDPpc	766	31655	241%	1.8%	1
LifeExp0	25.8	82.3	147%	0.4%	0.79
SurRate1	75.4	99.8	29%	0.1%	0.72
SurRate50	20.8	97.2	162%	0.3%	0.73
SurRate80	1.4	68.4	185%	0.6%	0.89

Notes: Sample contains 20 countries with time periods of average 113.6 years ranging from 1800 to 2008 (2265 observations). Total Sample growth is calculated as $(N_{2008}^{-1} \sum_i x_{2008} - N_{1800}^{-1} \sum_i x_{1800}) / N_{1800}^{-1} \sum_i x_{1800}$. See section 3.2 or the appendix for detailed information about the sample.

Table 1 gives an impression of the selected health indicators, their evolution over time, and their correlation with per capita income (GDPpc). All variables have increased enormously during the sample period. The table, however, clearly shows that the proxy for old age health, namely the survival rate 80, has increased most compared to the other survival rates and that its correlation with GDPpc is highest. This gives an first impression that the relationships between per capita income and survival rates may vary across age groups. Descriptively, it provides evidence for an accumulation mechanism as correlation between income and survivability increases with age at least till the age 80.

3. Empirical Strategy and Data

3.1. Empirical Strategy

This study successively investigates the long-run relationships between per capita income and the survival rates 1, 50, and 80. Life expectancy at birth is included for robustness reasons to consider an age independent and overall health indicator: If a significant relationship is detected for at least one of the survival rates, a significant relationship should also be detected for life expectancy at birth. If the investigated relationships are different for each age specific health measure, we can conclude that the income-to-health relationship changes over years of life. By reason of comparability, each age specific investigation is applied within the same estimation framework that is explained in the following.

The macro-empirical literature strongly dedicates itself to instrumental variables in order to address the potential endogeneity of macro 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, an instrumentation is impossible if the underlying relationship is heterogeneous across countries (Eberhardt and Teal, 2013). On these grounds, this study follows a strategy that relies on a panel time series approach, including a common factor framework.

Consider panel data for N countries, with a time dimension T , and let the empirical specification be

$$health_{it} = \alpha_i + \beta \ln GDPpc_{it} + u_{it} \quad \text{and} \quad u_{it} = \lambda_i' \mathbf{f}_t + \epsilon_{it}, \quad (1)$$

where i is the country index and t the time index. *health* is one of the selected age specific measures of population health and α_i is a country specific intercept. $\ln GDPpc$ is the natural logarithm of GDPpc.¹ u_{it} are unexplained components of *health* that are driven by a set of common factors \mathbf{f}_t with heterogeneous factor impacts λ_i and a residual ϵ_{it} .

The common factor framework $\lambda_i' \mathbf{f}_t$ accounts for the existing cross-sectional dependence in the variable series.² The framework is aimed to capture the evolution of unobserved common and stochastic components of the depended health variable. It is assumed that these components are interdependent across countries, that they follow non-stationary processes, that they have heterogeneous impacts across countries, and that they affect both the dependent health variable as well as explanatory GDP per capita.

Intuitively, the common factors may represent two types of components, global technological advances and common health shocks. The common technological evolution can be understood as cross country spillovers of technical developments that affect health outcomes through improved medical care and per capita income through the transmission of technological knowledge.³ Important global health shocks are the first and second World War as well as the *Spanish* Flu pandemic.⁴ These shocks surely have long-lasting impacts on both variables, health and per capita income.

As these common components may follow non-stationary processes, the common factor framework becomes relevant when analysing the relationship between non-stationary variables. It may allow an unbiased identification of the long-run income-to-health relationship.

The variables of interest, GDP per capita and the selected measures of population health, have stochastic trends, i.e. they contain unit roots.⁵ Therefore it is required to test for cointegration between the correspondent pairs of variable series in order to investigate an equilibrium relationship and to avoid spurious regression results (Granger and Newbold, 1974; Engle and Granger,

¹The log-level specification is motivated by the results of several studies. Preston (1975); Goldstein (1985); Deaton (2003) point out that the effect of income decreases as income increases.

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

³Cutler et al. (2006) argue that the ultimate determinants of mortality reductions are scientific advances and technical progresses rather than income increases. Similar to the empirical framework presented here, Eberhardt et al. (2013) implement a common factor robust framework in order to control for the cross country spillovers of R&D activities.

⁴The *Spanish* flu came around the globe by three waves during the years 1918, 1919 and 1920. Its fundamental impact on mortality rates is proofed in the literature (see Johnson and Mueller, 2002). To specifically concern these major shocks in the empirical investigation and to control for their impacts is usual in the related literature (see Swift, 2011). As such major shocks have long lasting impacts, they can not be seen as stationary processes.

⁵See appendix C for unit root test results.

1987). Testing on cointegration further ensures that the estimated long-run relationships are not driven by further omitted variables. This is a highly auxiliary fact as for the high number of early time periods data of relevant control variables are simply not available.

Specifically, the empirical analysis conducted in this study employs the Westerlund (2007) framework to test for cointegration. The Westerlund (2007) test is a second-generation test for cointegration. It relies on a reparameterized error correction representation that is given by

$$\begin{aligned} \Delta health_{it} = & \alpha_i + \kappa_i health_{it-1} + \phi_i^{gdp} \ln GDP pc_{it-1} + \phi_i^f f_{t-1} + \\ & \sum_{j=-q_i}^{p_i} \gamma_{ij}^{health} \Delta health_{it-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij}^{gdp} \Delta \ln GDP pc_{it-j} + \epsilon_{it} \quad . \end{aligned} \quad (2)$$

By this equation the parameter κ_i can be estimated irrespectively of arbitrary estimates of the equilibrium relationship. The estimated coefficient κ_i can be used for the calculation of adequate test statistics that indicate whether to reject or maintain the hypothesis of no error correction. Similar to Chang (2004), Westerlund (2007) uses a methodology to compute and bootstrap critical values that allow a common factor robust test for cointegration.

The Westerlund (2007) test contains four statistics, whereas two of them are group statistics that rely on weighted averages of individual estimates of κ_i . These indicate whether there is cointegration between pairs of variables for at least one country in the sample. The other two statistics pool information over all sample countries and thus test whether there is cointegration for the panel as a whole. Several studies point out that in the presence of country heterogeneity group estimates lead to a more accurate representation of the underlying relationship as they rely on individual slope coefficients (Pedroni, 1996; Haque et al., 1999; Eberhardt and Presbitero, 2015).

The Westerlund (2007) test is applied to all pairwise relationships between GDP per capita and one of the age specific measures of population health. Significant cointegration test results between GDP and the particular measure of population health indicate that GDP is a substantial health determinant for the particular population age group. If the test results vary across the age specific health measures, it can be concluded that the income-to-health relationship changes over the years of life.

If a cointegrating long-run relationship between GDP per capita and a particular measure of population health is detected by the Westerlund (2007) test, this study relies on the common correlated effects (CCE) mean-group estimator of Pesaran (2006) in order to estimate the mag-

nitude of the long-run relationship. The idea behind this estimator is to augment the estimation equation with cross sectional averages of both the dependent and independent variable in order to eliminate the differential effects of common factors. Thus, the CCE estimator is given by

$$health_{it} = \alpha_i + \beta_i \ln GDPpc_{it} + \eta_{1i} \overline{health}_t + \eta_{2i} \overline{\ln GDPpc}_t + \epsilon_{it} \quad , \quad (3)$$

where \overline{health}_t and $\overline{\ln GDPpc}_t$ are the corresponding cross sectional averages of both variables of interest. The mean-group CCE estimator estimates the relationship depicted in equation 3 for each country separately and then averages the individual long-run coefficients $\hat{\beta}_i$ over all countries. Thus, it also meets potential cross country heterogeneity in the income-to-health relationships.

Although the common factor framework addresses one type of the potential endogeneity, a remaining challenge for the econometric methodology is reverse causality. A large bulk of studies finds evidence that measures of population health positively affect per capita income.⁶ Theoretically, these studies mention the stimulation of human capital accumulation as well as the augmentation of labour productivity as important transmission channels of a causal health-to-income relationship. Consequentially, the present study has to provide evidence that the results of the empirical framework are not biased by reverse causality. Specifically, it will test whether the assumption of weakly exogenous regressors in the estimation specification holds.

Basically, the study follows Canning and Pedroni (2008) and Eberhardt and Presbitero (2015) in testing for weak exogeneity (W.E.) of the variables. In a first step, a disequilibrium term is calculated for the two selected *health* variables for that a causal dependency on per capita income is detected by the Westerlund (2007) test. The disequilibrium is predicted by the estimates of the Pesaran (2006) CCEMG. It's derivation includes the deterministic country intercepts and the predicted common components. The disequilibrium is given by

$$\hat{\epsilon}_{it} = y_{it} - \hat{\alpha}_i - \hat{\beta}_i x_{it} - \hat{\eta}_{1i} \overline{y}_t - \hat{\eta}_{2i} \overline{x}_t \quad . \quad (4)$$

In the second step, the disequilibrium term is embedded in an error correction model. Following Eberhardt and Presbitero (2015), cross sectional averages of all variables are included in order

⁶The debate on this issue is fed by Acemoglu and Johnson (2007). Instrumenting life expectancy by declines in mortality rates, it finds only an insignificant effect of life expectancy on output. Also Ashraf et al. (2008) doubt the existence of an health improving effect. However, a significant effect is documented by many studies such as Arora (2001, 2005); Bhargava et al. (2001); Bloom et al. (2004, 2014); Swift (2011).

to control for cross sectional dependence of the variables in first differences. Thus, the error correction framework becomes

$$\begin{aligned} \Delta y_{it} = & c_{yi} + \lambda_{yi} \hat{e}_{i,t-1} + \theta_{yi} \overline{\hat{e}_{i,t-1}} + \sum_{j=1}^p \gamma_{y,i,t-j}^y \Delta y_{i,t-j} + \sum_{j=1}^p \nu_{y,i,t-j}^y \Delta \overline{y_{i,t-j}} \\ & + \sum_{j=1}^p \gamma_{y,i,t-j}^x \Delta x_{i,t-j} + \sum_{j=1}^p \nu_{y,i,t-j}^x \Delta \overline{x_{i,t-j}} + \epsilon_{it} \end{aligned} \quad (5)$$

$$\begin{aligned} \Delta x_{it} = & c_{xi} + \lambda_{xi} \hat{e}_{i,t-1} + \theta_{xi} \overline{\hat{e}_{i,t-1}} + \sum_{j=1}^p \gamma_{x,i,t-j}^x \Delta x_{i,t-j} + \sum_{j=1}^p \nu_{x,i,t-j}^x \Delta \overline{x_{i,t-j}} \\ & + \sum_{j=1}^p \gamma_{x,i,t-j}^y \Delta y_{i,t-j} + \sum_{j=1}^p \nu_{x,i,t-j}^y \Delta \overline{y_{i,t-j}} + \epsilon_{it} \quad , \end{aligned} \quad (6)$$

where y and x abbreviations for the particular health measure and GDP per capita respectively. The parameters λ_{yi} or λ_{xi} capture the adjustment behaviour of the variables as response to deviations from the long-run equilibrium. The parameters $\gamma_{y,i,t-j}, \nu_{y,i,t-j}$ and $\gamma_{x,i,t-j}, \nu_{x,i,t-j}$ allow for short-run dynamics in the model.

Significant parameters λ_{yi} or λ_{xi} indicate that in the empirical model causality is running from x to y or from y to x respectively. Thus, a significant long-run equilibrium relationship implicates at least one λ -coefficient to be significant (Engle and Granger, 1987). Significant results for λ_{xi} indicate that the long-run coefficient estimates are biased by reverse causality.

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 (HMD). The HMD offers life table statistics for national populations of 37, prevailing European, countries. Its goal is to document the longevity revolution of the modern era.⁷ For most of the countries, data availability starts somehow in the 20th centuries, for few countries data is available quite longer.

As conventional for empirical works in the field of economic history, data for GDP per capita is taken from the New Maddison Project database (Bolt and van Zanden, 2014)⁸. Data on real per capita GDP is counted in 1990 international Dollars.

⁷The HMD data has been downloaded in August 2014: <http://www.mortality.org>

⁸Data used in this analysis was downloaded in January 2015: <http://www.ggdc.net/maddison/maddison-project/data.htm>

As required by the Westerlund (2007) methodology, 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 countries⁹. The number of individual periods range from 1800-2010 to 1958-2009 and is 113.6 on average.¹⁰

4. Empirical Results

4.1. Test for Cointegration

Table 2 shows the p-values of the four Westerlund (2007) test statistics for all the relationships between GDP per capita and one of the four measures of population health. The upper part includes the standard p-values and the lower part the p-values that are obtained with respect to common factor robust critical values.

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

Statistic	Dependent variables			
	LifeExp0	SurRate1	SurRate50	SurRate80
<i>P-value</i>				
Gt	0.005	0.109	0.000	0.996
Ga	0.000	0.192	0.001	0.063
Pt	0.046	0.871	0.021	0.938
Pa	0.002	0.587	0.004	0.172
<i>Common factor robust p-value</i>				
Gt	0.005	0.104	0.000	0.985
Ga	0.000	0.234	0.010	0.100
Pt	0.085	0.738	0.046	0.853
Pa	0.025	0.518	0.040	0.240

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.

Taking a look at the group statistics *Gt* and *Ga*, the reported p-values, whether they concern cross sectional dependency or not, clearly indicate error correction between GDP per capita and the survival rate 50. Conclusively, they also indicate error correction between GDP and life expectancy at birth. The corresponding p-values are zero or are close to zero indicating to reject

⁹Australia, Austria, Bulgaria, Canada, Denmark, England Wales Civilian, Finland, France Civilian, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, United States

¹⁰Further information about the sample can be found in appendix A.

the null hypothesis of no error correction. In contrast to these results, error correction is rejected between GDP and the survival rates 1 and 80.

Taking a look at the p-values of the pooled statistics Pt and Pa , it results that these reject the hypothesis of no error correction for the survival rate 50 only at the 5%-level and for life expectancy at birth at the 10%-level. The greater p-values of the pooled statistics can be a result of country heterogeneity in the panel, as pooled estimators may produce a less accurate representation of the underlying relationships. However, the test statistics of pooled estimations also reject cointegration for the survival rates of age 1 and 80 and in that way show a quite similar picture of age variations in the estimated relationships compared to the findings of the group statistics.

4.2. Long-Run Coefficient Estimates

Cointegration is only detected between per capita GDP and the survival rate 50 as well as between GDP and life expectancy at birth. Consequentially, this section provides quantifying estimates of long-run coefficients for these two relationships.

Table 3 presents the estimated coefficients along with the Pesaran (2004) test on cross sectional dependence of the residuals; the first row shows the results of the mean-group CCE suggested by Pesaran (2006) (CCEMG). The CCEMG indicates a positive and significant coefficient for both measures of health. The CD-statistic maintains the null of cross-sectional independence indicating that the CCEMG estimator eliminates cross-sectional dependence in the data series. The CCEMG estimator therefore appears as a satisfactory and preferred estimation framework. It indicates that an one percentage increase in per capita GDP raises life expectancy by 0.044 years and increases the number of survivors to age 50 by 0.072 out of 100 people.¹¹

For completeness, and to demonstrate that the CCEMG estimator outperforms alternative estimators, table 3 also includes the results of different estimation frameworks. They show that these estimators also yield positive significant coefficients but, in contrast to the CCEMG estimator they do not eliminate cross sectional dependence in the residual series.

The pooled CCE estimator pools information over all sample countries and thus does not account for potential country heterogeneity. The results of the pooled CCE estimator are shown in column two of table 3. However, similar to the results of the Westerlund (2007) test they are

¹¹The coefficients in table 3 are 4.403 and 7.165 respectively. Consider the level-log specification of the estimation equations, the quantitative effect is calculated as $\frac{\beta}{100}\% \Delta GDP_{pc}$.

Table 3: Long run coefficient estimates of per capita GDP on life expectancy and survival rate of age 50

Methodology	Dependent variable	
	LifeExp0	SurRate50
CCEMG	4.403 (1.057)	7.171 (0.647)
<i>CD-test</i>	-0.77	-0.25
CCEP	3.855 (1.243)	4.941 (2.180)
<i>CD-test</i>	-1.90	-2.56
CCEMG ^{trend}	2.579 (0.877)	4.078 (1.452)
<i>CD-test</i>	-4.67	-1.11
DCCEMG	2.377 (1.067)	3.103 (1.472)
<i>CD-test</i>	-7.74	-5.61

Notes: Standard errors in parenthesis. CCEMG and CCEP proposed by Pesaran (2006). The DCCEMG is augmented with one lag of all variables; the inclusion of more lags of averages as suggested by Chudik and Pesaran (2015) does not decrease the CD-statistic. CD-test denotes the Pesaran (2004) test statistic that indicates whether to maintain or reject the null of cross-sectional independence and that is distributed standard normal. All MG estimators use outlier robust averages of country coefficients. Heteroskedasticity robust standard errors are presented for the CCEP. ^{trend} This specification is augmented with a linear trend term.

still but less significant than the results of the mean-group estimator (CCEMG). The CD-test statistics reject cross sectional independence only at the 10%- and 5%-level respectively.

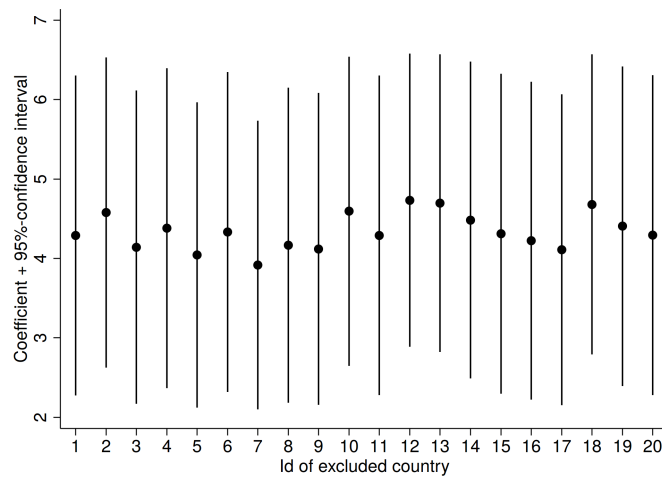
As argued by Eberhardt and Presbitero (2015), the inclusion of a country specific linear trend term may cause cross sectional dependence in the estimation residuals. Therefore the empirical analysis of this study has excluded such a linear trend term from the estimation framework. However, to check the robustness to such an augmentation, row 3 of table 3 presents the CCEMG augmented with an additional country specific linear trend term. The presented long-run coefficients are still significant, but the augmentation increases the CD-statistic and, at least for life expectancy as dependent variable, it no longer maintains the null of cross-sectional independence.

The dynamic CCEMG (DCCEMG) estimator suggested by Chudik and Pesaran (2015) extends the CCEMG estimator by augmenting the estimation equation with lagged values of the variables

and their cross sectional averages. Row 4 shows the results of the DCCEMG estimator. It also finds significant long-run coefficients, but the CD-test clearly rejects cross sectional independence.

As a further robustness check, it is investigated whether the coefficient estimates are driven by country outliers. Specifically, the CCEMG is re-estimated by successively excluding one country at a time from the sample. Figure 3 plots the 20 coefficient estimates for life expectancy at birth as dependent variable; the x-axis indicates the id of the excluded country. It shows that the coefficient estimates remain quite stable, and that all estimates are significantly greater than two indicating that the coefficient estimates are not driven by individual outliers.¹²

Figure 3: Robustness to country outliers for life expectancy at birth as dependent variable



4.3. Tests for Weak Exogeneity

With respect to the error correction framework depicted in equations 5, table 4 presents coefficient and test results for the parameters λ_y and λ_x . The results are separated for both health variables for that a cointegrating long-run relationship has been detected, the survival rate of age 50 and life expectancy at birth. The results of table 4 reject weak exogeneity of the health variable, but they do not reject weak exogeneity of GDP per capita. Thus, they suggest that the empirical model indicates causality running from income to health and not vice versa.

4.4. Graphical representation with an continuous age classification

In order to investigate life course variations in the income-to-health relationship, the previous analysis has been limited to a set of health indicators that represent three stages of life. In this

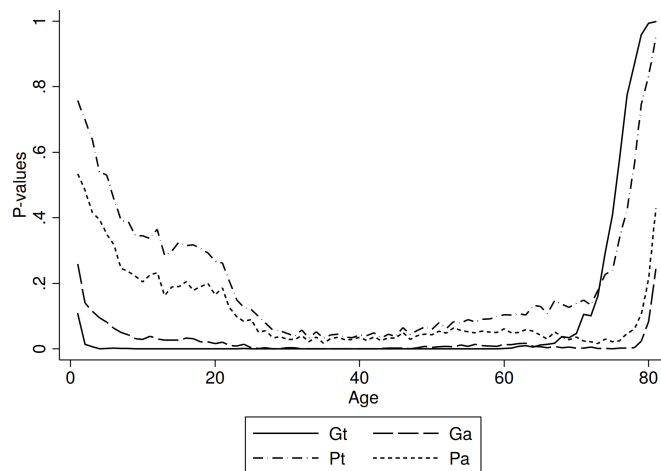
¹²Similar evidence can be provided for the survival rate 50 as dependent variable.

Table 4: Tests for weak exogeneity

<i>W.E. health</i>			<i>W.E. lnGDPpc</i>		
λ_y	T_λ	$\overline{T_{\lambda_i}}$	λ_x	T_λ	$\overline{T_{\lambda_i}}$
<i>Life Expectancy at birth</i>					
-0.249	-6.754	-3.152	0.002	1.831	0.790
<i>Survival Rate 50</i>					
-0.233	-6.501	-3.188	0.003	1.834	1.071

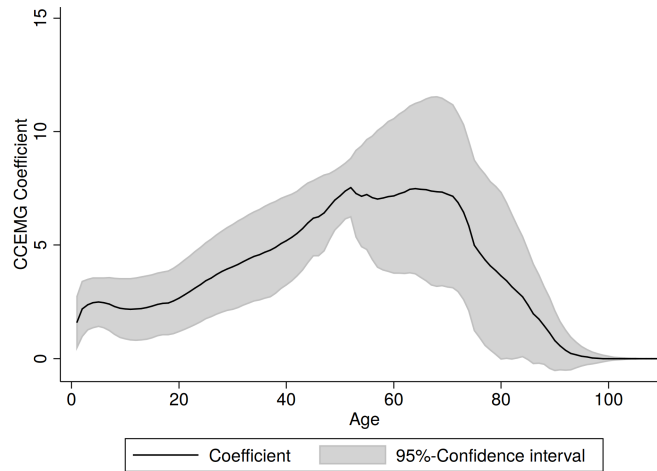
Notes: λ_y and λ_x are calculated as outlier robust means. T_λ is the t-statistic that corresponds to the mean-group coefficient λ_y or λ_x respectively. $\overline{T_{\lambda_i}}$ is the averaged t-statistic of the λ -coefficients across countries. Two lags of first differences are included to capture short run adjustments. Null hypothesis is weak exogeneity of the corresponding variable.

section, the results are presented graphically for a continuous age classification of population health. Figure 4 plots the common factor robust p-values of the four Westerlund (2007) test

Figure 4: Westerlund 2007 robust p-values for survival rates of ages 1 to 80 as dependent variables

statistics for survival rates of ages 1, 2, 3, ..., 80. The curves give a graphical impression of life course differences in the relationship between per capita income and health. For the age one, the p-values are greater than 0.1 rejecting cointegration between GDP and the survival rate. From that age they are steadily decreasing during youth and young adulthood and they clearly indicate cointegration for middle adulthood. From an age of around 50, the p-values again increase till they fully reject cointegration at an age of 80. Figure 5 also plots the long-run coefficients that are obtained by the CCEMG continuously for all survival rates. The figure clearly shows that the life course variations in the income-to-health relationship take an inverted U-shaped form. The effect

Figure 5: CCEMG-coefficients for survival rates 1 to 100 as dependent variables



of per capita income on survivability is small at infant ages,¹³ it increases during adolescence and adulthood, and reaches a maximum at the age 50. Afterwards, it first stagnates, it then decreases and diminishes.

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 is only concerned in survey studies and these studies may estimate a relative income effect rather than a general effect of absolute income. The present analysis is an attempt to address this weaknesses by transferring the life course perspective to a macro-empirical level with a long time horizon.

The big result of this study is that per capita income has a positive significant effect on life expectancy at birth, because it increases survival rates of the middle age groups. The analysis does not find a significant effect of per capita income on the infant survival rate. It neither finds an income effect on the survival rate 80 that has increased most compared to the other survival

¹³The figure plots slightly significant estimates for the survival rates of very young ages. Previously, it has been argued that such estimates are spurious as cointegration can not be detected for that ages. However, the figure is of value as it gives the best graphical impression of the investigated life course pattern of the income-to-health relationship.

rates during the sample period. Thus, it appears that other factors than income account for the enormous evolution of survival rates of very old age groups.

Concluding, it can be said that this study detects evidence for both hypotheses during several moments of life. While the *cumulative advantage* mechanism seems to be valid for the years of life till an age of around 50, the *age as leveller* hypothesis corresponds to the years of life afterwards.

The present study virtually replicates the results of House et al. (1994) but at a macro level. In a survey study these authors find a quite similar temporal ordering of both hypotheses during the years of life.

The results of this study have an important policy implication. The effectiveness of public health care in absorbing income effects ought to vary across age groups. Thus, makers of health care policy should take this age variations into account when balancing costs and quality of the public health care system. In particular, middle age groups are vulnerable to income shortages. Thus, the challenge is to establish well customized prevention schemes for these groups.

In addition, policy makers should not concern economic growth as a means of enhancing extreme longevity.

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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

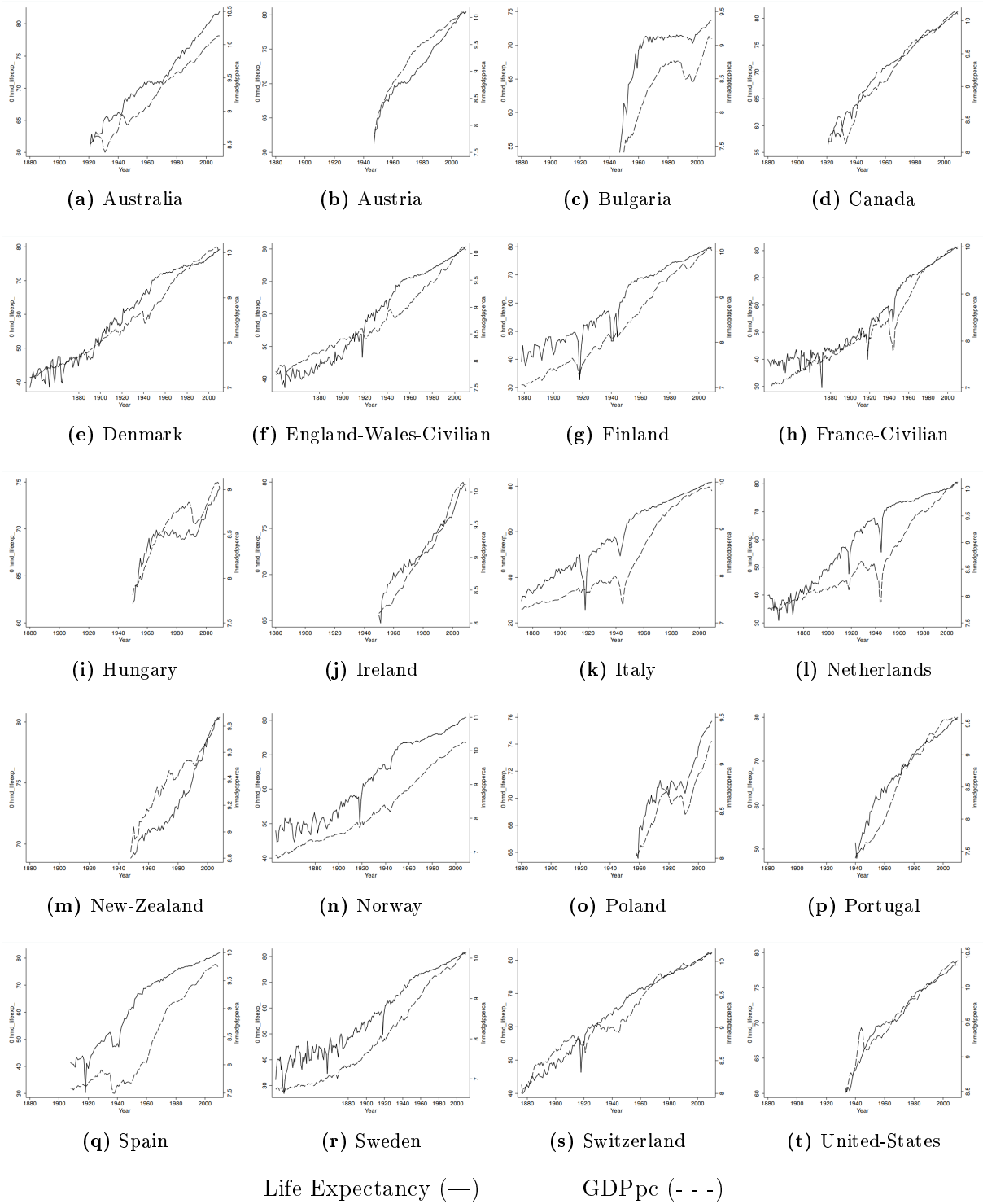
Notes: In the human mortality database sweden is the country with the longest series, starting from the year 1751. For one country, Iceland, data is available in the HMD, but not in the Maddison project database. Hence, it does not join the investigation conducted in this study.

Table A2: Summary statistics

Variable	Type	Mean	Std. Dev.	Min.	Max.
GDPpc	level	8206.456	6799.876	766	31655
	growth rate	0.018	0.044	-0.503	0.397
lnGDPpc	level	8.641	0.904	6.641	10.363
	growth rate	0.002	0.005	-0.052	0.06
LifeExp0	level	62.943	13.386	25.81	82.31
	growth rate	0.004	0.038	-0.478	0.39
SurRate1	level	93.552	6.187	75.399	99.758
	growth rate	0.001	0.009	-0.054	0.078
SurRate50	level	77.661	17.880	20.809	97.243
	growth rate	0.003	0.0586	-1.036	0.556
SurRate80	level	29.754	16.165	1.378	68.400
	growth rate	0.006	0.128	-1.852	0.71

Notes: *level* corresponds to the untransformed variable. *growth rate* is calculated as the sample average of $\frac{y_t - y_{t-1}}{y_{t-1}}$.

Figure A2: Individual time series plots



Notes: Figure A2 gives a graphical impression of the variables as time series. Life expectancy at birth is selected as comprehensive and representative indicator for survival conditions and population health. GDPpc denotes per capita income.

B. Test on Cross-Sectional Dependence

This study follows the perception that the common deterministic components of the variables series are cross sectional dependent (See Eberhardt and Teal, 2011, for a intuitive introduction to the topic). This implies that the evolution of each country series is correlated with the evolution observable in the other sample countries.

In order to provide evidence for existing cross sectional dependence (CD) in the variable series, table A3 presents the results of the CD-test proposed Pesaran (2004). The test, first, calculates the correlation coefficients $\hat{\rho}_{ij}$ for each correlation between the variable series of country i with country j . The test statistic is computed as

$$CD = \sqrt{\frac{2}{(N(N-1))}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \sqrt{T_{ij} \hat{\rho}_{ij}} \right) , \quad (7)$$

where T_{ij} is the number of observations the variable is available for both countries. The test is applied to both, the variables in levels and in first differences, as both are employed in the empirical analysis.

Table A3: Pesaran (2004) CD-test on levels and 1st differences

Variable	CD-test	p-value	corr	abs(corr)
<i>Levels</i>				
lnGDPpc	118.92	0.000	0.960	0.960
LifeExp0	116.55	0.000	0.938	0.938
SurRate 1	119.44	0.000	0.967	0.967
SurRate60	107.83	0.000	0.856	0.856
SurRate80	114.58	0.000	0.926	0.926
<i>1st Differences</i>				
Δ lnGDPpc	27.73	0.000	0.222	0.269
Δ LifeExp0	33.13	0.000	0.249	0.284
Δ SurRate1	27.36	0.000	0.223	0.257
Δ SurRate60	38.38	0.000	0.289	0.318
Δ SurRate80	114.58	0.000	0.926	0.926

Notes: *corr* denotes the average correlation coefficient and *abs(corr)* the absolute average correlation coefficient. The null hypothesis is cross sectional independence.

C. Unit Root Tests

The empirical analysis in this study investigates the long-run relationship between two cointegrated variables. It relies on the assumption that the time series in the data sample are non-stationary and 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 variables that are used in this analysis. The CIPSM-test allows to capture multiple unobserved common factors by augmenting the individual Dickey-Fuller equations with lagged cross sectional averages and their lagged differences of both, the variable of interest y and an additional regressors z_j . The Dickey-Fuller equations thus are

$$\begin{aligned} \Delta y_{it} = & \phi_{i0} + \phi_i^y y_{i,t-1} + \sum_{l=0}^p \gamma_{i,t-l}^y \Delta y_{i,t-l} + \phi_i^{\bar{y}} \bar{y}_{i,t-1} + \sum_{l=1}^p \gamma_{i,t-l}^{\bar{y}} \overline{\Delta y_{i,t-l}} \\ & + \sum_{j=0}^k \phi_{j,i}^{\bar{z}} \overline{z_{j,i,t-1}} + \sum_{j=0}^k \sum_{l=0}^p \gamma_{j,i,t-l}^{\bar{z}} \overline{\Delta z_{j,i,t-l}} \quad , \end{aligned} \tag{8}$$

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)

<i>deterministics : constant + trend</i>							
Variable	lnGDPpc	LifeExp0	SurRate1	SurRate50	SurRate80	Crit. Values	
						1%	5%
<i>k = 1</i>							
Z_1	LifeExp0	lnGDPpc	lnGDPpc	lnGDPpc	lnGDPpc		
<i>Stat</i>	-2.107	-2.022	-2.188	-1.999	-1.912	-2.96	-2.79
<i>k = 2</i>							
Z_1	LifeExp0	lnGDPpc	lnGDPpc	lnGDPpc	lnGDPpc		
Z_2	SurRate1	SurRate1	LifeExp0	LifeExp0	LifeExp0		
<i>Stat</i>	-2.135	-2.234	-2.340	-2.341	-1.884	-3.10	-2.91
<i>deterministics : constant</i>							
Variable	lnGDPpc	LifeExp0	SurRate1	SurRate50	SurRate80	Crit. Values	
						1%	5%
<i>k = 1</i>							
Z_1	LifeExp0	lnGDPpc	lnGDPpc	lnGDPpc	lnGDPpc		
<i>Stat</i>	-1.489	-1.557	-1.963	-1.416	-1.465	-2.54	-2.36
<i>k = 2</i>							
Z_1	LifeExp0	lnGDPpc	lnGDPpc	lnGDPpc	lnGDPpc		
Z_2	SurRate1	SurRate1	LifeExp0	LifeExp0	LifeExp0		
<i>Stat</i>	-1.301	-1.793	-1.750	-1.549	-1.404	-2.71	-2.53
<i>deterministics : constant</i>							
Variable	Δ	Δ	Δ	Δ	Δ	Crit. Values	
	lnGDPpc	LifeExp0	SurRate1	SurRate50	SurRate80	1%	5%
<i>k = 1</i>							
Z_1	LifeExp0	lnGDPpc	lnGDPpc	lnGDPpc	lnGDPpc		
<i>Stat</i>	-3.613	-4.387	-4.041	-4.290	-4.119	-2.54	-2.36
<i>k = 2</i>							
Z_1	LifeExp0	lnGDPpc	lnGDPpc	lnGDPpc	lnGDPpc		
Z_2	SurRate1	SurRate1	LifeExp0	LifeExp0	LifeExp0		
<i>Stat</i>	-3.398	-4.035	-4.113	-4.263	-3.905	-2.71	-2.53

Notes: k indicates the number of additional regressors. Z_1 and Z_2 indicate the sample variables that are selected as additional regressors. 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.