Inequality in Life Expectancies across Europe and the US

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Abstract

We use harmonized household panel data from Europe and the US and a 3-state survival model to provide comparable measurements of education and gender inequalities in total, healthy, and unhealthy life expectancies at age 50. Common across countries, the education advantage in total life expectancy is larger for males but the education advantage in (fewer) unhealthy years is larger for females. Counterfactual decompositions show that these results arise because the education advantage in conditional survival rates is relatively more important for males, while the education advantage in better health transitions is relatively more important for females. Across countries, the US stands out with the largest education gradient in healthy life expectancy.

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1 Introduction

The study of economic inequality has attracted a great deal of attention in the last decades. New data and methods have been developed, providing a fairly good picture of the differences in income and wealth inequality across countries, see the recent survey by Alvaredo et al. (2018). Unfortunately, less is known about the range of inequalities in health outcomes and mortality across countries. Health inequality might be more important in terms of welfare—see De Nardi et al. (2017)—, it has first order implications for public policy, and it is likely to become more relevant in the coming years with the aging of population. Furthermore, efforts to understand the determinants of health inequality can benefit from both the differences and the similarities to be found across countries.

This paper puts together harmonized panel data to compare, for the first time, the inequality in total life expectancy (LE), healthy life expectancy (HLE), and unhealthy life expectancy (ULE) at age 50 between education and gender groups across Continental Europe, England, and the United States. In particular, we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE), the English Longitudinal Study of Ageing (ELSA), and the Health and Retirement Study (HRS) for the time period 2002-2015. In our main analysis, the healthy state is defined as the absence of limitations in activities of daily living (i.e., no ADLS). For education, we group individuals into those with or without a college degree. For every country-education-gender group, we estimate a three-state (good health, bad health, death) continuous time duration model tailored to match micro data obtained in discrete time at irregular intervals. The model estimates are then used to build country-specific three-state life tables by gender and education

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starting at age 50, which in turn are used to compute life expectancies for the different demographic groups.

We start by documenting the pervasiveness of several patterns across countries. First, as is well known, individuals who are more educated experience higher LE. Second, the education gradient in LE (the difference between college and non-college individuals) is larger for males than for females: the average across countries is 3.4 years for males and 2.2 years for females. Third, the education gradient is larger in HLE than in total LE, which means that college educated individuals spend less time in bad health despite living longer. And fourth, this education advantage in (fewer) unhealthy years is stronger among females: college educated females (males) spend 1.7 (0.6) fewer years in bad health. Finally, note that these last two results imply that there is a "compression of morbidity" across education groups: the more educated not only live longer but also spend less time in bad health. This is especially pronounced among females: every extra year of life for more educated females (males) is associated with almost 6 (almost 2) fewer months in bad health.

Next, we use the estimated three-state survival model to provide a decomposition of mortality and morbidity dynamics that helps identify the drivers of the aforementioned interactions between education and gender. For instance, college educated individuals may live longer because (a) they have better health at age 50, because (b) they transit less frequently to and/or recover faster from poor health states with higher mortality, or because (c) they survive longer conditional on their health. To the best of our knowledge this is the first paper to carry out a cross country comparison of these decompositions. Common across countries we find that, after age 50, education confers an advantage both in transition rates between health states and in survival conditional on health, but that their relative strength varies across genders: the education advantage in survival is relatively larger for men and the education advantage in health transitions is relatively larger for women.

Our data also display noteworthy heterogeneity across countries. Overall, taking into account both gender and education dimensions, inequality is largest in Eastern Europe and smallest in Scandinavia. The US stands out as the country with the largest inequality across education groups in HLE, which arises because it has very large education advantage in transition rates between health states. Different from other regions, Mediterranean females with college education have a very small advantage in total LE, but they have the largest advantage in (fewer) unhealthy years.

Finally, it is natural to ask whether spending in the national health system may help mitigate health inequalities. The countries in our sample differ substantially in this dimension: in 2010 public spending on health ranged from 4.6% of GDP in Poland (the lowest in our sample) to 8.8% in Denmark (the highest). We relate this variation with the cross-country heterogeneity in the educational gradients discussed above. We find that higher public spending on health correlates with lower inequality in LE and higher inequality in ULE across education groups. Inspecting the mechanisms through our counterfactual life expectancies, we conclude that public spending on health is associated with a smaller education advantage in survival rates conditional on health but it is unrelated to the education advantage in health transitions. While no causality can be inferred from these relationships, a tentative interpretation is as follows: public spending on health increases life duration for the less educated mainly in the bad health state, which leaves the education gradient in HLE unchanged and increases the education advantage in (fewer) unhealthy years.

We acknowledge potential problems in using longitudinal survey data for survival analysis. While the SHARE, ELSA, and HRS surveys have carefully designed sampling frames and provide exit interviews to separate attrition from death events, there is always the possibility of biases in sample design, in response rates at baseline, or in sample retention. Furthermore, most of these surveys sample from the non-institutionalized population, which may yield additional biases if entry into nursing homes occurs at different health thresholds across different education groups. We discuss these issues in more detail in Section 5 and validate our survey data by, first, comparing our estimated life tables by gender to the ones from population data and, second, by running an attrition analysis based on covariates that predict mortality. The Online Appendix provides all the details on this validation exercise in Section E. In the paper, we only include results for the US, England, and ten SHARE countries whose life tables match the population tables best and with no predictable attrition bias.

Related Literature. The size of the education gradients of LE and HLE are consequential for many economic questions. First, because gradients are big, forecasts of future gains in LE and HLE need to keep track of changes in education attainment of the underlying population. For instance, according to Case and Deaton (2017), the growth in college attainment explains almost one half of the reduction in age-adjusted mortality in the US between 1910 and 2000. Second, the redistributive power of retirement pensions may be partly eroded by the longer life expectancies of richer individuals (Brown (2002) or Fuster et al. (2003)). Third, the HLE gradient is crucial for effective outcomes in postponing retirement age for a sustainable pay-as-you-go retirement system (see Blundell et al. (2016)). And fourth, the ULE gradient is critical for planning long-term care as well as for predicting related expenses (De Nardi et al. (2016), Bueren (2017), or Braun et al. (2019)).

There are reliable measures of the education gradient in LE in the US using both data from death registers (Meara et al. (2008)) and from household surveys (Pijoan-Mas and Ríos-Rull (2014)). However, this is less so in Europe for two reasons. First, death registers in Europe do not record information on education. Despite this, some recent papers (Avendano et al. (2011) or Mackenbach et al. (2008)) have made progress by linking the death registers with census data to obtain education and gender-specific death rates. However, the advantage of this census-linked mortality data set is somewhat reduced because the lack of older population (above 80 years of age) and imperfect data harmonization across countries (with often non-representative country samples). And second, regarding survey data, only the European Community Household Panel has been used (ECHP, covering years 1994 and 2000 in Majer et al. (2010)). A limitation of the ECHP is its small number of old individuals, the lack of exit interviews for distinguishing attrition from death events, and the absence of data for East European countries. Besides the ECHP, HLE gradients in Europe are documented only by Maki et al. (2013) applying the Sullivan method to census-linked mortality data.

A recent literature has brought important findings about the widening gap of education gradients of LE in the US (Meara et al. (2008) and Montez et al. (2011)), the increase in mortality rates of low-educated white males (Case and Deaton (2017)), or the larger decline in mortality in richer counties for the 50+ population (Currie and Schwandt (2016)). The increase in the education gradient of mortality has also been documented in several European countries (Mackenbach et al. (2015b) and de Gelder et al. (2017)). Our work does not explore cohort phenomena as the time span of our underlying data is relatively short. However, our methods can be used to analyze time changes when these longitudinal surveys span longer time periods (and can be already applied to the HRS panel).

2 Methodology

In longitudinal surveys, the time span between two consecutive observations that form an individual transition is often not perfectly regular across countries, waves, and individuals. This Section describes the multistate duration model we use to estimate health transitions from microdata obtained at irregular intervals, the estimation method, and the use of the estimated model to compute LE, HLE, and ULE education gradients and decompositions.

Statistical Model. We define 3 states: 0 (dead), 1 (alive-unhealthy), 2 (alive-healthy). The death state is absorbing, while individuals are allowed to transit between healthy and unhealthy states as they age.[1] A typical measurement at wave w is (a_w, h_w, x_w) where a_w is age, h_w is health state, and x_w are socio-economic variables. Every individual in our sample is observed in at least two (not necessarily consecutive) waves, so our empirical model is based on the transition probabilities $P(h_{w+1}|a_{w+1}, a_w, h_w, x_w)$, where $w+1$ is the next wave of observation for each individual, which is at an arbitrary distance $a_{w+1} - a_w$ from wave w.

We interpret the transitions between states as the outcome of independent competing risks in continuous time, but we assume that the underlying hazard rates are constant between birthdays and that at most one transition occurs between any two birthdays and between an observation (wave) and the nearest birthday. To obtain the likelihood contribution for $P(h_{w+1}|a_{w+1}, a_w, h_w, x_w)$, we need to combine probability contributions for: (i) complete 1-year intervals between birthdays, (ii) incomplete intervals between $\left[a_w, \text{int}(a_w) + 1\right]$ and $\left[\text{int}(a_{w+1}), a_{w+1}\right]$, where $\text{int}(a)$ is a function that returns the integer part of any age a. For instance, an individual who is observed in two waves separated by two and a half years will provide one or two contributions of type (i) and two contributions of type (ii). Furthermore, we need to integrate over all possible trajectories between (a_w, h_w) and (a_{w+1}, h_{w+1}) because health is allowed to change every year but it is unobserved between interviews.

For contributions of type (i) we specify two multinomial logits for the transition probabilities from each state $i = 1, 2$ at birthday a to state $j = 0, 1, 2$ at birthday $a + 1$. The covariates are age a itself and potentially variables for socio-economic status x. To ease notation, let's abstract from x. Define $a \in \{50, 51, ..., \bar{a}\}$, where $\bar{a}$ is the maximum age, and $f_{ij}(a) = \beta_{ij0} + \beta_{ij1}a$. Normalizing $\beta_{ii0} = \beta_{ii1} = 0$, $f_{ij}(a)$ represents the log-odds ratio of moving from health status i to health status j over remaining in i which is assumed to be a linear function in age. The probability $p_{ij}(a)$ that an individual with health $i \in \{1, 2\}$

[1] Our model differs from the often used illness-to-death models with irreversible transitions to bad health. In Table D.13 in the Appendix we show that, if one ignores the possibility of recovery from bad health, the education gradients in life expectancy tend to be larger and the compression of morbidity across education groups tend to disappear.

at birthday a transits into health $j \in \{0,1,2\}$ within a year is

$$p_{ii}(a) = \frac{1}{1+e^{f_{ik}(a)}+e^{f_{i0}(a)}}, \quad p_{ik}(a) = \frac{e^{f_{ik}(a)}}{1+e^{f_{ik}(a)}+e^{f_{i0}(a)}}, \text{ and } p_{i0}(a) = \frac{e^{f_{i0}(a)}}{1+e^{f_{ik}(a)}+e^{f_{i0}(a)}},$$

where $k \neq i, 0$. For contributions of type (ii), define $\tilde{p}_{ij}(a,d)$ as the probability that and individual with health $i \in \{1,2\}$ and age a transits into health $j \in \{0,1,2\}$ within a fraction d of a year (before reaching birthday $a+1$). To compute $\tilde{p}_{ij}(a,d)$, first recover the hazard rates $\lambda_{ij}(a)$ from

$$\begin{aligned} 1 - p_{ik}(a) - p_{i0}(a) &= e^{-(\lambda_{ik}(a)+\lambda_{i0}(a))}, \\ p_{ik}(a) &= \frac{\lambda_{ik}(a)}{\lambda_{ik}(a)+\lambda_{i0}(a)}\left[1-e^{-(\lambda_{ik}(a)+\lambda_{i0}(a))}\right], \end{aligned}$$

so that, for $k \neq i, 0$,

$$\begin{aligned} \tilde{p}_{ii}(a,d) &= e^{-(\lambda_{ik}(a)+\lambda_{i0}(a))d}, \\ \tilde{p}_{ik}(a,d) &= \frac{\lambda_{ik}(a)}{\lambda_{ik}(a)+\lambda_{i0}(a)}\left[1-e^{-(\lambda_{ik}(a)+\lambda_{i0}(a))d}\right], \\ \tilde{p}_{i0}(a,d) &= \frac{\lambda_{i0}(a)}{\lambda_{ik}(a)+\lambda_{i0}(a)}\left[1-e^{-(\lambda_{ik}(a)+\lambda_{i0}(a))d}\right]. \end{aligned}$$

Given the objects $p_{ij}(a)$ and $\tilde{p}_{ij}(a,d)$, we write the likelihood $P(h_{w+1}|a_{w+1},a_w,h_w)$ of any given individual transition as

$$\begin{aligned} P(h_{w+1}|a_{w+1},a_w,h_w) &= \begin{bmatrix} \mathbb{1}_{h_w=1} & \mathbb{1}_{h_w=2} \end{bmatrix} \begin{bmatrix} \tilde{p}_{11}(\text{int}(a_w),d_1) & \tilde{p}_{12}(\text{int}(a_w),d_1) \\ \tilde{p}_{21}(\text{int}(a_w),d_1) & \tilde{p}_{22}(\text{int}(a_w),d_1) \end{bmatrix} \\ & \prod_{a=\text{int}(a_w)+1}^{\text{int}(a_{w+1})} \begin{bmatrix} p_{11}(a) & p_{12}(a) \\ p_{21}(a) & p_{22}(a) \end{bmatrix} \\ & \begin{bmatrix} \tilde{p}_{11}(\text{int}(a_{w+1}),d_2) & \tilde{p}_{12}(\text{int}(a_{w+1}),d_2) & \tilde{p}_{10}(\text{int}(a_{w+1}),d_2) \\ \tilde{p}_{21}(\text{int}(a_{w+1}),d_2) & \tilde{p}_{22}(\text{int}(a_{w+1}),d_2) & \tilde{p}_{20}(\text{int}(a_{w+1}),d_2) \end{bmatrix} \begin{bmatrix} \mathbb{1}_{h_{w+1}=1} \\ \mathbb{1}_{h_{w+1}=2} \\ \mathbb{1}_{h_{w+1}=0} \end{bmatrix}, \end{aligned}$$

where $\mathbb{1}$ is an indicator function with $d_1 = \text{int}(a_w) + 1 - a_w$, and $d_2 = a_{w+1} - \text{int}(a_{w+1})$. Similar expressions for the likelihood contribution of a given individual transition can be derived when the information on health h_w or/and h_{w+1} is incomplete (the survival status is known but not whether the individual is healthy or unhealthy).

Finally, in the data we observe N of such individual transitions. Because we consider those N transitions independent, the full likelihood can be written as

$$p(H|\boldsymbol{\beta}) = \prod_{n=1}^{N} P(h_{w+1}^{n}|a_{w+1}^{n}, a_{w}^{n}, h_{w}^{n}), \tag{1}$$

where H represents all the health transitions in the sample and $\boldsymbol{\beta}$ is the vector of β_{ijl} parameters.

Estimation. In order to reduce the uncertainty of estimated parameters in samples with a small number of observed transitions, we rely on Bayesian techniques and constrain the space of possible $\boldsymbol{\beta}$ to satisfy a set of priors: conditional on surviving, the probability of remaining in good health and the probability of moving from bad to good health both decrease with age; conditional on being in good or bad health, the probability of surviving decreases with age; and the probability of dying is greater when in bad health than in good health. Then, the posterior distribution of $\boldsymbol{\beta}$ is

$$p(\boldsymbol{\beta}|H) \propto p(H|\boldsymbol{\beta}) \cdot p(\boldsymbol{\beta}), \tag{2}$$

In order to sample from the posterior distribution, we use Markov Chain Monte-Carlo (MCMC) methods with a random-walk Metropolis algorithm. See Appendix A for a detailed description of all procedures.

Computing life expectancies. The posterior distribution of parameter estimates delivers a distribution of transition probabilities or multi-state life tables $p_{ij}(a)$ for each country-gender-education sample. Given a multi-state life table we apply standard formulas described in Appendix B to compute total life expectancy (LE) at age 50 and its two components HLE and ULE, i.e. the expected number of years spent in the good and bad health state, where by construction LE = HLE + ULE. We report medians and standard errors of these measures implied by the posterior distribution.

Decomposing differences in life expectancies. The fact that two individuals from different populations differ in their expected LE is the result of asymmetries in transition probabilities across states or in differences in initial conditions. For example, college educated people could live longer because they are healthier initially, because they tend to transit to states with higher mortality less frequently, or because they survive longer conditional on health. Of course, each of these forces could be at play simultaneously, moving the difference in LE in opposite directions.

In order to disentangle the sign and the strength of these forces, we follow Pijoan-Mas and Ríos-Rull (2014) and compute *counterfactual education gradients* in LE, HLE, and ULE as if each gender-education subgroup differed only in its initial health *distribution* at age 50, or in health *transitions* conditional on being alive, or in probabilities of *survival* conditional on health.[2] That is, for each gender, we first compute the share of individuals in good and bad health state for the whole population and for each education level. Then we estimate the transition probabilities for the whole population and for each education subgroup. Finally, we compute counterfactual life expectancies for each education subgroup if it had: a) the transition probabilities of the whole population but its true education-specific initial condition; b) the survival probabilities conditional on health and the initial condition of the whole population but its true transition probabilities conditional on being alive; c) the transition probabilities conditional on being alive and the initial condition of the whole population but its true survival probabilities conditional on health.

3 Data

We merge all available waves of the SHARE data plus waves 6 to 11 of HRS and waves 1 to 7 of ELSA in order to use data in a comparable time frame. Every individual-wave *observation* refers to a transition between the given wave and the next available (not necessarily consecutive) one, keeping track of age, the date of interview, health status or the date of death in the case the individual did not survive, as well as gender and education. We exclude from the sample individuals without any transition (with only one observation or in their last wave) and those individuals with below 50 and above 90 years of age. Individuals with missing information on health but known survival status are kept as they also provide valuable likelihood contributions. We focus on education as a measure of socio-economic status because it is a good approximation to lifetime income and on gender because it is an important dimension of inequality across individuals. *College education* is defined as a completed degree at a tertiary educational institution (college or university) with ISCED 1997 codes 5-6, whereas *non-college education* corresponds to all the remaining ISCED codes 0-4.[3]

A person in the *unhealthy state* is defined as having limitations with at least one of

[2]See Solé-Auró et al. (2015) for a similar decomposition of differences in disease-specific mortality between Europe and the US into contributions from larger prevalence at age 50, larger incidence after age 50, or lower survival.

[3]See Table C.1 in Appendix C for a comparison of the education distribution in our country samples with the one from the population from Eurostat and Census Bureau for the relevant age groups.

the following six activities of daily living (ADL): dressing (including putting on shoes and socks), walking across a room, bathing or showering, eating, getting in and out of bed, and using the toilet. Limitations in ADL are widely used in the economic literature (Dwyera and Mitchell (1999) for labor supply, Ameriks et al. (2019) for savings, or Braun et al. (2019) for long-term care insurance).[4] For completeness, we also consider two alternative definitions of bad health. First, a more severe definition of bad health that considers the *unhealthy state* as having limitations with at least two ADLs. Second, a less severe definition of bad health that considers the *unhealthy state* as having functional limitations with several activities that require some degree of mobility. See Section 5 for details.

In Table D.1 in Appendix D we report for every country the number of waves for which the survey was run, the interval of years for which the survey was conducted, and the number of respondents. The HRS and ELSA samples, with around 30,000 and 15,000 respondents, respectively, are much larger than any country sample in SHARE which range between around 2,100 and 6,900 individuals. In order to obtain more precise estimates from larger samples and to better organize our results, we group SHARE countries into four geopolitical regions and estimate the model with the pooled data separately for Western Europe (Austria and France), Eastern Europe (Czechia, Estonia, Poland and Slovenia), Mediterranean (Italy and Spain), and Scandinavia (Denmark and Sweden). Results for individual countries are presented in Appendix D. These SHARE countries are selected because their samples provide life tables that are good matches to population life tables. See Appendix E for details on this validation exercise of our SHARE, ELSA and HRS samples. The Appendix also contains sections on parametric vs. non-parametric survival functions, sampling frames, and attrition.[5]

4 Results

This Section presents results on life expectancy (LE), healthy life expectancy (HLE), and unhealthy life expectancy (ULE) of four demographic groups: males and females with and without college education. Define the *education gradient* as the difference between a longevity outcome of the college educated minus the same outcome of the non-college educated individuals of the same gender in the same country. We report gradients sepa-

[4]The ADL scale was first proposed by Katz et al. (1963). For international comparability, Chan et al. (2012) find good equivalence for the ADL items between the HRS and SHARE, but less so with ELSA. For an educational gradient in the incidence of difficulties in ADLs see Cutler and Lleras-Muney (2010).

[5]Some of the waves include sample refreshments while other waves do not. This could raise a concern that some cells may be scarcely populated in our samples. See Appendix E.4 for a detailed discussion.

rately for the four European regions, England, and the US.[6] We first document patterns which are pervasive across countries, and then we report a few salient differences.

Education gradients in life expectancy. Table 1 shows the average education gradients in LE for males (Panel A, column 1) and females (Panel B, column 1) in each region. As is well-known, the LE education gradient is always positive for both males and females. More importantly, the gradient tends to be larger among males than among females (on average across all countries 3.4 vs. 2.2 years).

Education gradients in healthy and unhealthy life expectancy. Tables 2 and 3 display the education gradients in HLE and ULE. Education gradients in HLE are always positive and larger than the gradients in LE, and more so among females: on average across countries, the education gradients in HLE and LE are 3.9 and 2.2 years for females and 4.0 and 3.4 years for males.[7] This means that the gradient in ULE is negative (more educated individuals spend fewer years in bad health) and much larger for females (-1.7 years vs. -0.6 years for males).[8]

Decomposition of education gradients. Tables 1-3 also report the decomposition for the LE, HLE, and ULE gradients when the education types differ only in their health distribution at age 50 (columns denoted with a subscript D), only in health transitions conditional on being alive (T), or only in survival conditional on health (S).

First, differences in health across education groups at age 50 are inconsequential as most individuals in their fifties are healthy (all estimates in D-columns are very small).

Second, the decomposition of LE gradients in Table 1 shows that college educated individuals tend to live longer because of advantages in both health transitions and survival. Among males, the advantage in survival is very significant and explains around 3/4 of the observed gradients in LE (2.7 out of 3.4 years). In contrast, differences in survival rates between education groups are relatively less important for females as they account for

[6] The actual levels of the life expectancy for each of the four demographic groups in each country are reported in Table D.2 and D.3 of Appendix D, while the levels pooling across education groups are reported in Table D.4. The education gradients country by country are reported in Table D.5. The corresponding life tables for each group and country are available online at the authors' web pages.

[7] For several definitions of health and socio-economic status, Crimmins and Cambois (2003) also document a greater gradient for HLE than LE. Maki et al. (2013) apply the Sullivan method to census-linked mortality data and calculate educational gradients in healthy life expectancy between the ages of 30 and 79 years with similar results in all countries. Using data from the ECHP, Majer et al. (2010) find larger HLE gradients and a big female advantage in LE (however, they do not have data on Eastern Europe, England and the US).

[8] Note that the identity LE = HLE + ULE carries over to the education gradients.

about 3/5 of the LE gradient (1.3 out of 2.2 years). Note that gender differences in the education gradient in LE are entirely driven by the survival gradient (1.3 years females, 2.7 years males) as the education gradient driven by health transitions is very similar for both males and females.[9]

Third, the decomposition of the HLE gradients in Table 2 shows that educational advantage in health transitions is as large as the education advantage in survival for males (1.9 and 2.0 years, respectively). Instead, for females the gradient in transitions is much larger (2.8 years) while that of survival is small (1.0 year).

And finally, more educated individuals spend fewer years in bad health because of their better health transitions and despite their better survival functions. The total negative education gradient in ULE in Table 3 is composed from a positive gradient due to mortality differences (0.7 and 0.3 for each gender, respectively) and from a large, negative gradient due to health transitions (-1.1 and -1.9 years, respectively). In other words, absent the differences in health transitions, the college-educated individuals would display larger (not smaller) ULE due to to their better survival rates in bad health. Finally, note that the total education advantage in unhealthy years is much larger among females (-1.7 vs. -0.6 years) and that is mostly due to their greater advantage in health transitions.

Cross-country differences. Tables 1-3 also show heterogeneity across countries. The most significant findings are as follows. Overall, taking into account both gender and education dimensions, inequality in LE, HLE and ULE is largest in Eastern Europe and smallest in Scandinavia. The US stands out as the country with the largest education gradient in HLE. Our decompositions show that this happens because in the US the advantage conferred by education through transition rates between good and bad heath states is very large.[10] Finally, different from other regions and countries, Mediterranean females with college education have a negligible advantage in total LE compared to non-college females. However, they have a strikingly large advantage in (fewer) unhealthy years as they spend 3.5 fewer years in the bad health state (1.6 vs 5.1).

[9] With the exception of the Mediterranean countries, where the education advantage in health transitions turns out to be substantially larger among females.

[10] Differences in health transitions in the US also make a large contribution to the male gradient in LE. This result is related to Pijoan-Mas and Ríos-Rull (2014), who find that the gradient in LE in the US is almost exclusively explained by the different health transitions across education groups. Our results differ from theirs in that we still find a role for the education gradient in survival, while they do not. This is likely due to their use of self-rated health measure, a very good predictor of mortality.

5 Discussion

Compression of morbidity across education groups. The "compression of morbidity" hypothesis states that improvements in longevity over time are associated with decreases in morbidity.[11] But the compression question is also of interest in cross-sectional comparisons of populations that differ by socio-economic status or gender. Our analyses of the education gradients and their decompositions show that there is a "compression of morbidity" across education groups (education groups that live longer spend fewer years in bad health), and that this compression occurs because the education advantage in health transitions is sufficiently important relative to the educational advantage in conditional survival rates.

Interactions between education and gender. At the same time, we find that the compression of morbidity across education groups is larger for females: the education advantage in LE is larger for males but the education advantage in (fewer) unhealthy years is larger for females. A careful look at our decompositions shows that we can trace interactions between gender and education to a simple regularity: across countries, the education advantage in conditional survival is relatively more important for males and the education advantage in health transitions is relatively more important for females.

Gender gaps. The interaction between gender and socio-economic status sheds new light on a related question. It is well-known that females have longer LE than males and that the gender gap or female advantage in LE is associated with more, not less morbidity, a pattern often described as "women get sicker but men die quicker".[12] A double-difference identity implies that the difference in gender gaps in LE, HLE, or ULE between the non-college and college populations must equal the difference in education gradients between males and females.[13] Our results in Tables 1-3 show that the education gradient in LE

[11]Fries (1980) was the first to note that the delay in mortality in the US may have been associated to an even larger delay in the onset of disease or disability, thereby reducing the average time spent in poor health. This was in contrast to Gruenberg (1977), who argued that delays in mortality are associated to smaller delays in the onset of disease and hence to increases in ULE. Recent results by Cutler et al. (2013) confirm the compression of morbidity in the US since the 1990's. See Fries et al. (2011) for a survey.

[12]Note that this represents a "failure of compression" of sorts, see Lorber and Moore (2002).

[13]In particular, letting the c and nc subscripts denote college and non-college and m and f denote male and female we can write:

$$\left(\mathrm{LE}_{nc,f} - \mathrm{LE}_{nc,m}\right) - \left(\mathrm{LE}_{c,f} - \mathrm{LE}_{c,m}\right) = \left(\mathrm{LE}_{c,m} - \mathrm{LE}_{nc,m}\right) - \left(\mathrm{LE}_{c,f} - \mathrm{LE}_{nc,f}\right),$$

and the same applies for HLE and ULE.

is 1.2 years larger for males than for females, while the (negative) education gradient in ULE is 1.1 years larger for females in absolute value. This means that the gender gap in LE is 1.2 years larger for the non-college population than for the college population while the (negative) gender gap in ULE is 1.1 years larger for the non-college. In other words, the "women get sicker but men die quicker" phenomenon is much more apparent when comparing females and males without college education. Indeed, we find that this phenomenon is hardly present for men and women with college education.[14]

Cross-country differences in the literature. Our comparison of life expectancies between the US and Europe is novel. Interestingly, the US does not display particularly large inequality in LE across education groups as compared to Europe. This may be surprising given the prevalence of "deaths of despair" across less educated Americans—see Case and Deaton (2017). However, our sample refers to the 50+ population, while the evidence on "deaths of despair" refers to middle aged (45-54) individuals. The US does show the largest levels of inequality in HLE for the 50+, which comes from the fact that the US displays the largest education gradient in health transitions but not in survival. Our results on differences in LE education gradients across European countries are qualitatively in line with other studies, although there are some important differences. In particular, using census-based mortality studies, Mackenbach et al. (2008), Mackenbach et al. (2015a) and Avendano et al. (2011) document that mortality differences are largest in Eastern Europe, intermediate in Nordic countries, and smallest in Mediterranean. Mackenbach (2017) refers to these results as the "Eastern Disaster", the "Nordic Paradox", and the "Southern Miracle". The term "Nordic Paradox" highlights that one would expect the lowest inequality in mortality to arise in countries with low income inequality and strong welfare states, while the term "Southern Miracle" underscores the low inequality in mortality in countries where the welfare state is not so strong. Our results do confirm the "Eastern Disaster" but neither the "Nordic Paradox" nor the "Southern Miracle". There are several possible reasons for the discrepancy between our results and the ones obtained in the census-based mortality studies quoted above. First, the age range of the underlying populations are different: 50+ in SHARE, HRS, and ELSA, and 30-79 in the census-based mortality studies. Second, several of the census-based mortality studies are represented only by provinces or cities (Italy and Spain). And third, we have different countries representing Scandinavia (Denmark and Sweden compared to Finland and Norway).

[14]As shown in Table D.6 in Appendix D, the gender gap in ULE among the college educated is very small (0.3 years) and not statistically significant for the average of countries, and it is actually negative in the Mediterranean and Scandinavia.

Cross-country differences and public spending on health. The national health system is possibly the main policy tool available to governments to tackle health inequalities. The countries in our study differ substantially in their public spending on health. As a first step towards understanding how health policy affects different socio-economic groups, we explore the co-variation of the education gradients in life expectancies for our 12 countries with the fraction of GDP devoted to public spending on health. In particular, we regress the gradients of our three life expectancies in each country against the ratio of public spending on health over GDP in 2010. The top panel in Table 4 shows a negative and strong correlation between public spending on health and the gradient in LE for males. The estimated regression coefficient is -0.44, which indicates that the education gradient in LE for males is 1.8 years smaller when the public spending on health goes from 4.6% of GDP (the lowest in the sample, Poland) to 8.8% (the highest in the sample, Denmark). These 1.8 years represent 53% of the average LE gradient for males. We explore the relationship between public spending on health and the gradients of HLE and ULE separately.[15] We find that all the effect goes to the ULE gradient: countries with more public spending on health tend to have smaller education gradients in LE, the same gradient in HLE, and larger (in absolute value) gradients in ULE.

These results are interesting but have to be taken with caution. The small number of data points prevents us from controlling for other relevant variables, which may lead to omitted variables bias. For instance, governments that spend more in health may also be spending more on education, welfare, or long-term care, which in turn may affect the gradients. While no causality can be inferred from these correlations, one way to interpret the result is that public spending on health allows less privileged individuals to live longer but in worse health, which would be consistent with public spending on health improving the survival of low educated individuals in bad health but not improving their health transitions. This effect of public spending on health is apparent in the counterfactual gradients LE_{S} and ULE_{S} but not in LE_{T} and ULE_{T} (see the central and bottom panels in Table 4). Consistent with this interpretation, recent quasi-experimental evidence from the 2008 Oregon Health Insurance Experiment finds no improvements in measured physical health outcomes among low income individuals in the US who have been randomly granted access to Medicaid (Baicker et al. (2013)).

Finally, for females, public spending on health is also negatively related to the edu-

[15]Because of the identity LE = HLE + ULE and the linearity of the covariance operator, the regression coefficients for the gradients of HLE and ULE add up to the regression coefficient for the gradient of LE, which allows for a clean decomposition. In practice, however, this sum is not exact in Table 4 because we use the median and not the mean of the posterior distribution of the gradients in LE, HLE and ULE.

cation gradient in LE with a point estimate of -0.12, which is smaller and less precisely estimated than for males. One possible interpretation is that public spending on health may diminish the education gradients in LE by reducing the education advantage in survival and, as discussed in Section 4, survival differences across education groups matter less for females.

The interpretation of education gradients. First of all, we stress that our education gradients are measured at age 50 and may hence differ from education gradients at earlier ages. For instance, Case and Deaton (2017) uncover the prevalence of "deaths of despair" across less educated middle aged (45-54) Americans. This may imply education gradients in the U.S. that are larger at age 30 than at age 50. Second, and more importantly, our study cannot distinguish between how much these gradients come from a causal effect of education and how much come from selection into education. Furthermore, causality and selection may differ across countries and genders. For instance, only 8.8% of females aged 55 to 74 hold a college degree in Italy, while the figure is 27.3% in Sweden. This probably means that college education represents a more selective measure of socio-economic status among Italian than among Swedish females. Relatedly, the income premium associated with a college degree differs across countries and genders. This means that the extent to which college education is associated with more financial resources varies across countries. The US stands out in this respect. For instance, while median household income is 2.18 (2.47) times larger for college than for non-college US males (females), median income is 1.50 (1.67) times larger for college than for non-college Italian males (females). This could happen because labor market differences across countries allow for the education advantage to generate different wage returns. But it could also happen because a college degree implies a different level of selectivity across countries and genders.[16]

Alternative definitions of bad health. As a robustness exercise, we re-estimate our model with two alternative definitions of bad health. In particular, we first redefine bad health as a state in which the respondent has problems with at least 2 ADLs (ADL2+). Second, we redefine bad health as a state in which individuals report functional limitations with at least 3 activities that require some degree of mobility (MBL3+).[17] ADL2+ is, by

[16]We give a more detailed picture of the incidence of college education and of the college premium in household income across countries and genders in Appendix C.

[17]Respondents in the three surveys are asked whether they face difficulties with (a) walking 100 meters, (b) sitting for 2 or more hours, (c) getting up from a chair after sitting for long periods, climbing one or more flights of stairs without resting, stooping, (d) kneeling or crouching, (e) reaching or extending the arms above the shoulder level, (f) pulling or pushing large objects like a living room chair, (g) lifting or

construction, a more severe definition of bad health than our benchmark, while MBL3+ turns out to be a less severe definition of bad health. In particular, the average incidence of bad health across all years, genders, and countries is 7.5% with ADL2+, 14.5% with the benchmark, and 33% with MBL3+.

We report the results of these estimations in the Appendix, Tables D.7, D.8, and D.9, and Tables D.10, D.11, and D.12, respectively. For ADL2+, the LE gradients are nearly identical as they should (small differences might arise due to the initial distribution of individuals into health groups) but the HLE gradients are somewhat smaller (in all countries and genders). That is, there is a slightly lower compression of morbidity across education groups. In the decompositions, we find that the gradient in transitions is slightly less important. In the case of MBL3+, we get the opposite pattern: the gradients in HLE are larger and the importance of the gradients in transitions is larger than in our benchmark case.

All in all, we observe that the education gradient in HLE increases when the definition of bad health becomes less severe. One way to interpret these findings is that education protects healthy people from the onset of mild symptoms of bad health, but it does not protect individuals from the evolution of these mild symptoms into more complicated conditions. Further research might focus on a more granular definition of health—taking into account differences in health transitions and survival across different levels of dependency, see for instance Amengual et al. (2020)—and a multivariate definition of healthy life expectancy.

Nursing homes and sampling biases. Most HRS-like surveys sample from the non-institutionalized population, and there is evidence of differential entry into nursing homes according to socio-economic status.[18] Hence, one may worry that missing the frail elderly in long-term care facilities could lead to biases in our gradients. For instance, it could happen that the threshold of health to enter these institutions is lower for the less educated. This would leave the population living in the community with a higher fraction of bad-health individuals among the less educated. In this case, the education gradient of health outcomes in the survey would be biased upwards compared to the overall population. Additionally, if our samples suffered attrition related to entry to institutions, and

carrying weights over 5 kilos like a heavy bag of groceries, and (h) picking up a coin from a table. Our MBL3+ variable takes value one if the respondents answers yes in at least three of these questions.

[18]For instance, Lakdawalla et al. (2003) show that in the US, controlling for health, entry into nursing home is lower for the more educated and higher income individuals. For SHARE countries and also controlling for health, Laferrère et al. (2013) show that low-wealth individuals (but not low-income) are more likely to enter nursing homes.

more educated individuals were more likely to enter an institution when they transit to bad health, then we would be missing more of the transitions to bad health by the more educated, which may again biases the gradient upwards. There are three reasons to think these potential biases are not quantitatively important in our study. First, although most of our surveys do not sample from institutionalized population at baseline, individuals are followed when they transit into an institution. Therefore our samples do contain a fraction of people living in institutions. Second, incidence of institutionalized population is very low until age 85 (less than 2% of individuals according to data from the Eurostat Census Hub). Hence, this is a phenomenon linked to the very old, which has a relatively small effect on life expectancy gradients between age 50 and 90. And third, a comparison of the education distributions in our samples with those in the population does not reflect biases related to age (see Appendix C). If there was a large differential entry into nursing homes by education, the representativeness of education in our samples would deteriorate with age, which is not the case.

6 Conclusions

In this paper we study LE, HLE, and ULE across Continental Europe, England, and the United States, focusing on the interaction between education and gender. We develop statistical methods that are suitable for panel data obtained at irregular intervals. A compression of morbidity arises as a return to education. On the one hand, college-educated individuals experience a lower mortality in the bad health state, which prolongs its duration. But on the other hand, education has even greater health-protecting effect as the college-educated visit bad health less often and hence have lower average ULE. Our 3-state model allows for transitions from the unhealthy state back to the healthy state, which is a relevant aspect of the advantage conferred by higher education. A larger compression of morbidity occurs among females because their educational advantage in health transitions is relatively more important. Another implication of this is that college females live longer than college males with hardly any increase in unhealthy years, in partial rebuttal of the well-known "women are sicker but men die quicker" phenomenon. Beyond these common patterns there is heterogeneity across countries and further research may want to exploit these phenomena to better understand the underlying causes of health inequality. Finally, we also find that countries with more public spending on health tend to have smaller education gradients in LE, the same gradient in HLE, and larger (in absolute value) gradients in ULE. One way to interpret these correlations is that public spending on health may reduce the education advantage in survival rates in bad health. Consequently, more public spending on health does not change the education advantage in HLE while it might increase the education advantage in ULE.

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Tables

Table 1: Decomposition of LE education gradients

	A. Males				B. Females			
	LE	LE_D	LE_T	LE_S	LE	LE_D	LE_T	LE_S
Western Europe	3.9	0.0	0.8	3.2	1.7	0.0	0.6	1.1
	(0.7)	(0.0)	(0.2)	(0.7)	(0.6)	(0.0)	(0.2)	(0.7)
Eastern Europe	4.0	0.1	0.7	3.3	3.9	0.0	0.8	3.0
	(0.8)	(0.0)	(0.2)	(0.8)	(0.6)	(0.0)	(0.2)	(0.6)
Mediterranean	3.0	0.0	0.7	2.6	0.7	0.0	1.4	-1.6
	(1.0)	(0.0)	(0.3)	(1.0)	(1.1)	(0.0)	(0.3)	(1.2)
Scandinavia	2.1	0.0	0.7	1.6	2.3	0.0	0.8	1.5
	(0.7)	(0.0)	(0.2)	(0.7)	(0.6)	(0.0)	(0.2)	(0.7)
England	3.4	0.1	1.1	2.5	1.2	0.0	0.5	0.6
	(0.6)	(0.0)	(0.2)	(0.6)	(0.6)	(0.0)	(0.1)	(0.6)
US	3.6	0.1	1.4	1.9	3.2	0.1	1.3	2.0
	(0.4)	(0.0)	(0.1)	(0.5)	(0.4)	(0.0)	(0.1)	(0.4)
Average	3.4	0.1	0.8	2.7	2.2	0.0	0.8	1.3
	(0.4)	(0.0)	(0.1)	(0.4)	(0.4)	(0.0)	(0.1)	(0.4)

Notes: LE: education gradient in life expectancy at age 50. Counterfactual education gradients when education types differ only in: health distribution at age 50 (LE_D), health transition conditional on being alive (LE_T), probability of survival (LE_S). The entries in the Table report the median (and the standard deviation in parenthesis) of the distribution of the corresponding life expectancy gradient arising from the posterior distribution of the estimated $\boldsymbol{\beta}$ parameters.

Table 2: Decomposition of HLE education gradients

	A. Males				B. Females			
	HLE	HLE_D	HLE_T	HLE_S	HLE	HLE_D	HLE_T	HLE_S
Western Europe	4.6	0.1	2.1	2.5	3.0	0.1	2.2	0.7
	(0.7)	(0.0)	(0.5)	(0.6)	(0.7)	(0.0)	(0.5)	(0.5)
Eastern Europe	4.3	0.2	1.7	2.5	5.1	0.1	2.7	2.1
	(0.7)	(0.0)	(0.4)	(0.6)	(0.6)	(0.0)	(0.4)	(0.4)
Mediterranean	3.4	0.0	1.6	1.8	4.1	0.0	4.6	-0.7
	(1.0)	(0.0)	(0.6)	(0.7)	(1.1)	(0.0)	(0.7)	(0.7)
Scandinavia	2.9	0.1	1.8	1.1	3.7	0.1	2.4	1.1
	(0.7)	(0.0)	(0.4)	(0.6)	(0.7)	(0.0)	(0.4)	(0.5)
England	4.7	0.3	2.9	1.6	3.0	0.2	2.4	0.3
	(0.6)	(0.0)	(0.4)	(0.4)	(0.6)	(0.0)	(0.4)	(0.4)
US	5.3	0.3	3.2	1.5	5.1	0.4	3.5	1.3
	(0.4)	(0.0)	(0.3)	(0.4)	(0.4)	(0.0)	(0.3)	(0.3)
Average	4.0	0.2	1.9	2.0	3.9	0.1	2.8	1.0
	(0.3)	(0.0)	(0.2)	(0.3)	(0.4)	(0.0)	(0.3)	(0.2)

Notes: HLE: education gradient in healthy life expectancy at age 50. Counterfactual education gradients when education types differ only in: health distribution at age 50 (HLE_D), health transition conditional on being alive (HLE_T), probability of survival (HLE_S). The entries in the Table report the median (and the standard deviation in parenthesis) of the distribution of the corresponding life expectancy gradient arising from the posterior distribution of the estimated $\boldsymbol{\beta}$ parameters.

Table 3: Decomposition of ULE education gradients

	A. Males				B. Females			
	ULE	ULE_D	ULE_T	ULE_S	ULE	ULE_D	ULE_T	ULE_S
Western Europe	-0.8	-0.1	-1.3	0.7	-1.3	-0.1	-1.6	0.4
	(0.4)	(0.0)	(0.3)	(0.2)	(0.4)	(0.0)	(0.4)	(0.3)
Eastern Europe	-0.3	-0.1	-1.0	0.9	-1.2	-0.1	-1.8	0.9
	(0.3)	(0.0)	(0.2)	(0.2)	(0.4)	(0.0)	(0.3)	(0.3)
Mediterranean	-0.4	-0.0	-0.9	0.7	-3.5	-0.0	-3.2	-0.9
	(0.5)	(0.0)	(0.3)	(0.3)	(0.4)	(0.0)	(0.5)	(0.5)
Scandinavia	-0.8	-0.1	-1.1	0.5	-1.4	-0.1	-1.6	0.4
	(0.3)	(0.0)	(0.3)	(0.2)	(0.3)	(0.0)	(0.3)	(0.2)
England	-1.3	-0.2	-1.8	0.8	-1.8	-0.2	-1.9	0.3
	(0.3)	(0.0)	(0.3)	(0.3)	(0.4)	(0.0)	(0.3)	(0.3)
US	-1.7	-0.2	-1.8	0.4	-2.0	-0.3	-2.2	0.7
	(0.2)	(0.0)	(0.1)	(0.1)	(0.2)	(0.0)	(0.2)	(0.2)
Average	-0.6	-0.1	-1.1	0.7	-1.7	-0.1	-1.9	0.3
	(0.2)	(0.0)	(0.1)	(0.1)	(0.2)	(0.0)	(0.2)	(0.2)

Notes: ULE: education gradient in unhealthy life expectancy at age 50. Counterfactual education gradients when education types differ only in: health distribution at age 50 (ULE_D), health transition conditional on being alive (ULE_T), probability of survival (ULE_S). The entries in the Table report the median (and the standard deviation in parenthesis) of the distribution of the corresponding life expectancy gradient arising from the posterior distribution of the estimated $\boldsymbol{\beta}$ parameters.

Table 4: Correlations between education gradients and public spending on health

A. Males			B. Females		
LE	HLE	ULE	LE	HLE	ULE
-0.44	-0.08	-0.35	-0.12	0.09	-0.18
(0.19)	(0.23)	(0.14)	(0.35)	(0.34)	(0.25)
LE_T	HLE_T	ULE_T	LE_T	HLE_T	ULE_T
0.13	0.34	-0.20	0.12	0.26	-0.12
(0.09)	(0.19)	(0.11)	(0.10)	(0.28)	(0.19)
LE_S	HLE_S	ULE_S	LE_S	HLE_S	ULE_S
-0.55	-0.41	-0.13	-0.23	-0.21	-0.01
(0.21)	(0.16)	(0.06)	(0.39)	(0.21)	(0.18)

Notes: Each entry reports the regression coefficient of the corresponding life expectancy gradient on public spending on health over GDP. The top block refers to the actual gradients, the middle block refers to the counterfactual gradients in which education groups only differ in transitions (subscript T), and the bottom block refers to the counterfactual gradients in which education groups only differ in conditional survival (subscript S). Standard errors in parenthesis.