The impact of medical progress on the increasing inequality in life expectancy

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Abstract

We present a novel life-cycle model, grounded in demographic principles, to examine the influence of medical technological progress on the rise in life expectancy and income among different socioeconomic groups. Our preliminary findings indicate that the expanding disparity in life expectancy between income groups, as well as the growing income inequality among educational groups, can be attributed to the medical technological advancements that emerged with the cardiovascular revolution in the 1970s.

1. Motivation

Over the past decades we have seen in many countries an increasing inequality not just in terms of income and wealth, but also in terms of health and life expectancy (OECD, 2017). More recent data from the US also show that this trend continues, and the gap becomes even larger when more income groups are considered (National Academies of Sciences, Engineering, and Medicine, 2015). For instance, the projected gap in life expectancy between the top and the bottom one percent is 14 years for the 1960 birth cohort (Chetty, 2016).

In this paper we aim at understanding the drivers of the increasing inequality trend not just in terms of income but also in terms of life expectancy. To do so, we model the life-cycle for a succession of birth cohorts in an economy with ongoing productivity growth and medical progress, the latter rendering health care more effective. Members of each cohort are drawn from a time-constant distribution in regard to the initial characteristics, consisting of the initial frailty level, an effort of attending schooling, and the ability to convert education into human capital. Individuals face three stages of their life-course —education, working life, and retirement— the length of these stages being determined endogenously through the initial selection of the educational attainment and through the labor supply path. In addition, individuals decide on a consumption path and a path of health investments, determining the most likely age at death (or modal age at death).

2. Methodology and data

To investigate the impact of medical progress on inequality, we propose a novel life cycle model that is based on a survival frailty model (Vaupel et al., 1979), in which individuals decide about their educational attainment, consumption path, labor supply, health investments, and maximum longevity. Individuals are aware that health investments increase the probability that they are dying at a higher age. Within the proposed model, the disparities among individuals in terms of their education, income, life expectancy, and wealth arise from a combination of individual choices and external circumstances that shape their demographics and economic decisions. To address these variations in our model, we use three unobservable characteristics (learning ability level, effort of schooling, and frailty level) that are equally distributed across each birth cohort at the beginning of life. These characteristics enable us to consider that with better demographic and economic conditions faced by each birth cohort, individuals in lower educational groups tend to be negatively selected (e.g. Goldring et al, 2016).

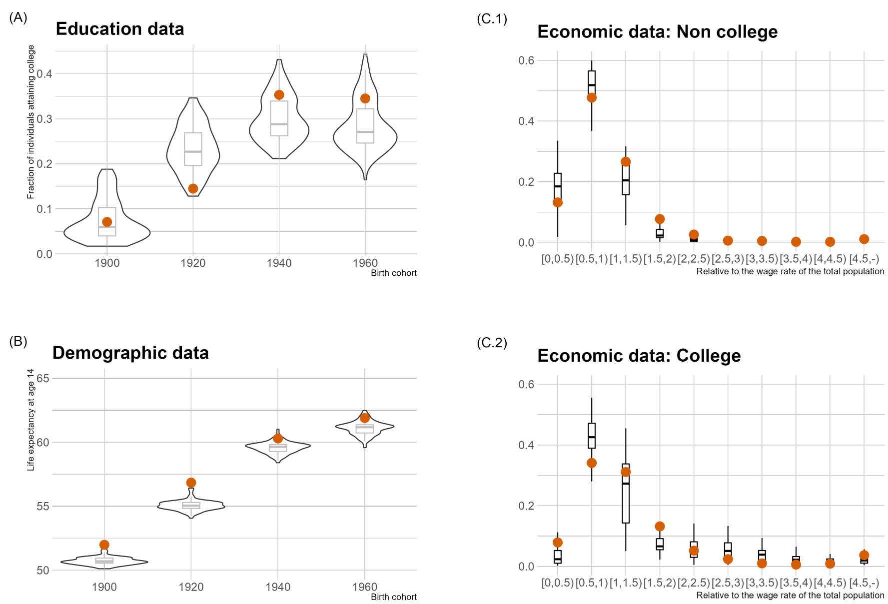

Figure 1: Model fit.

Notes: Red dots depict actual data on education (A), life expectancy at age 14 (B), and the wage rate distribution for college and non-college educated workers aged 40-44 years in the year 2000 (C). Source: Data on educational attainment by birth cohort is taken from Goujon et al (2016); cohort life expectancy data has been collected from the US Social Security Administration (Bell et al., 1992). The wage rate per hour worked for college and non-college educated individuals aged 40-44 in the year 2000 is taken from IPUMS-CPS data. The wage rate per hour worked is derived after controlling for race, occupation, industry, and state.

Given our life-cycle model, the unobservable characteristics have been calibrated, using the Bayesian melding approach with the IMIS algorithm (Poole and Raftery, 2000; Raftery and Bao, 2010), to replicate the evolution of the educational distribution, the distribution of income by educational group, the increase in life expectancy by birth cohort, and the increasing mortality gap by educational group for US males born between 1900 and 1960. The economic data on income is taken from IPUMS-CPS, education data from the WIC Human Capital Explorer (Goujon et al, 2016), US mortality rates data by educational attainment from US-CDC, and cohort-life tables from Bell et al. (1992). As an illustration, Figure 1 displays the fit of the calibrated model to education, demographic, and economic data for selected US birth cohorts (1900, 1920, 1940, and 1960). The figure is divided into four panels. Panel A is devoted to education data, panel B to demographic data, and panels C.1 and C.2 to economic data. In panels A and B we combine violin plots with boxplots in order to provide information about the distribution of the data as well as the 25th percentile, the median, and the 75th percentile of the model results. Panels C.1 and C.2 only use boxplots. Thus, Figure 1 shows that the model is capable of replicating the data (red dots) well, and that, as a consequence, it is a valid tool for studying the drivers of the increasing demographic and income inequality.

3. Preliminary results

Using the posterior distribution of the calibrated parameters, we first generated a large number of random draws of characteristics for the 1900, 1920, 1940, and 1960 birth cohorts. Second, we derived the life cycle decisions and the age-specific mortality rates associated to each individual (given the characteristics). Figure 2 shows our preliminary results for the relationship between the life expectancy at age 14, LE(14), and the wage rate (in logs) at ages 40–44 for the selected US birth cohorts. Note that the life expectancy and wage rates are the result of individual human capital and health investments. To control for the variation within and across educational groups for each birth cohort, we consider two educational groups: non-college (lower panel) and college (top panel). The results show that, for younger cohorts, life expectancy exhibits a stronger gradient in the wage rate. See the slope of the blue lines, which represents the unconditional correlations.

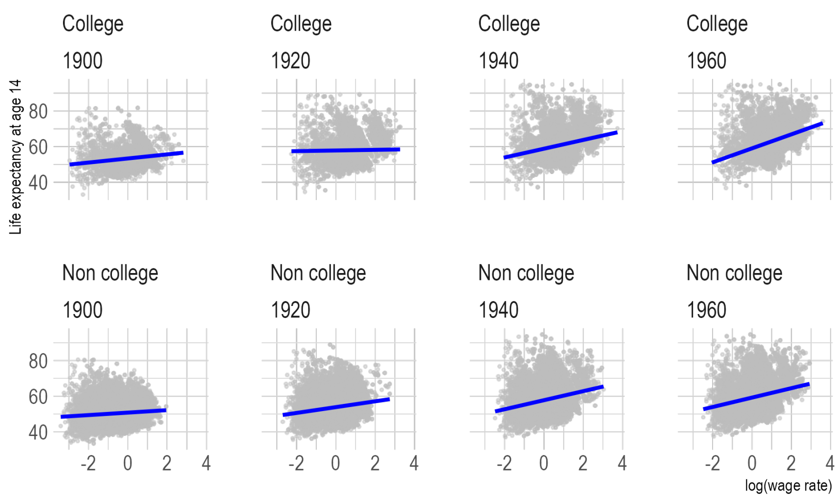

Figure 2: The relationship between life expectancy at age 14 and the wage rate (in logs) at ages 40–44 for four US Cohorts born between 1900 and 1960 by educational attainment.
Source: Authors simulations. Notes: The gray dots are generated with the life cycle model with frailty. Blue lines represent the unconditional correlations for each birth cohort and educational group.

To assess the correlation between life expectancy and the wage rate, we have regressed the life expectancy at age 14, LE(14), of an individual i, of cohorts s and with education e on the log of the wage rate, $\log(wH)$, using the following fixed-effects model

$$\mathrm{LE}_{ise}(14) = \beta_s \log(wH)_{ise} + \gamma_e + \lambda_s + u_{ise} \tag{1}$$

where β_s captures the impact of a 1 percent increase in the wage rate on life expectancy for the cohort born in year s, (γ_e, λ_s) take into account individual differences by education and by birth cohort, respectively, and u is the residual term. The estimated $\hat{\beta}_s$ values suggest that, for individuals born in 1900, having a wage rate twice as high as the average corresponds to an additional 0.877 years of life expectancy at the age of 14. For those born in 1960, this difference in wage rates is associated with a substantially larger gain of 2.015 years in life expectancy at the same age.

3.1. Ongoing work

To complete our analysis, we are conducting counterfactual scenarios in which we simulate the absence of productivity growth and medical progress. This strategy serves two main purposes: first, it enables us to study the respective influences of productivity growth and medical progress on the distribution of life expectancy and income across different cohorts. Second, it allows us to quantify the contributions of each factor to the increasing inequality in life expectancy based on income levels and educational attainment.

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