PROGRAM ON THE GLOBAL DEMOGRAPHY OF AGING AT HARVARD UNIVERSITY

Working Paper Series

The Impact of Medical Innovations on Longevity Inequality

Ivan Frankovic and Michael Kuhn

April 2018

PGDA Working Paper No. 155
http://www.hsph.harvard.edu/pgda/working/

Research reported in this publication was supported by the National Institute on Aging of the National Institutes of Health under Award Number P30AG024409. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

The impact of medical innovations on longevity inequality*

Ivan Frankovic[†] and Michael Kuhn[‡]

April 17, 2018

Abstract

We study medical progress and skill-biased productivity growth as drivers of longevity inequality from a theoretical life-cycle as well as from a macroeconomic perspective. To do so, we develop an overlapping generations model populated by heterogeneous agents subject to endogenous mortality. We model two groups of individuals for whom differences in skills translate into differences in income and in the ability to use medical technology effectively in curbing mortality. We derive the age-specific individual demand for health care based on the value of life, the level of medical technology and the market prices. Calibrating the model to the development of the US economy and the longevity gap between the skilled and unskilled, we study the impact of rising effectiveness of medical care in improving individual health and examine how disparities in health care demand and mortality emerge as a consequence. Furthermore, we explore the role of differential income growth. We pay particular attention to the macroeconomic feedback from price changes, especially to medical price inflation.

Keywords: education gradient in mortality, inequality, life-cycle model, health care spending, (skill-biased access to) medical progress, overlapping generations, skill-biased earnings growth.

JEL-Classification: D15, I11, I12, I24, J11, O33, O41.

---

*The paper was conceived and partly developed while Ivan Frankovic was visitor to the Harvard T.H. Chan School of Public Health. Their hospitality is gratefully acknowledged. Thanks also to David E Bloom for making this visit possible and to Ray Miller, Neha Bairoliya as well as Jessica Sullivan for helpful comments and support during my stay. Financial support for this research by the Austrian Science Fund under grant P 26184-G11 is gratefully acknowledged. The responsibility for any errors lies entirely with us.

[†]Wittgenstein Centre (IIASA, VID/ÖAW, WU), Vienna Inst. of Demography; ivan.frankovic@oeaw.ac.at.

[‡]Wittgenstein Centre (IIASA, VID/ÖAW, WU), Vienna Inst. of Demography; michael.kuhn@oeaw.ac.at.

1 Introduction

While increasing disparities in longevity across socioeconomic groups in the US have been extensively documented (Hummer and Hernandez 2013; Chetty et al. 2016; Case and Deaton 2017),[1] there is an ongoing debate on the drivers of the underlying health-related inequality (e.g. Woolfe and Braveman 2011; Truesdale and Jencks 2016; Case and Deaton 2017). With much of the empirical work revolving around the identification of socio-economic drivers of health-related inequality in a static or comparative static context, somewhat less attention has been devoted to the dynamic forces behind the ongoing widening of the longevity gap. Whereas different trends to health-related behaviours may explain the gradient at the individual level, differential impacts of technological development are likely to constitute another prominent force behind the dynamics.

Two trends, in particular, are likely candidates as drivers of the longevity gap: First, skill-biased technological progress across many sectors of the economy has been extensively documented to generate a widening income gap in advantage of the skilled and educated [see Acemoglu and Autor (2011) for an overview]. Income differences have been extensively documented to generate differences in the consumption of health care and, more specifically, in the access to highly effective state-of-the-art health care (Getzen 2000; Bago d'Uva and Jones 2009; Vallejo-Torres and Morris 2013). Owing to their higher propensity to consume health care, wealthier individuals then tend to participate more strongly in the benefits from medical progress (Goldman and Lakdawalla, 2005). Second, even at the same level of consumption of health care, medical progress is prone to lead to divergent medical outcomes and trends to life expectancy if individuals from higher socioeconomic groups are able to utilize medical advances more effectively in lowering mortality (Phelan and Link 2005, Glied and Lleras-Muney 2008, Avitabile et al. 2011, Lange 2011, Hernandez et

[1] See also OECD (2017) for evidence on similar trends across other industrialised countries.

al. 2018) or have access to higher quality treatments (Fiva et al. 2014).[2]

In this paper, we set out a theoretical model that accommodates skill-biased income growth and skill-biased access to medical technology as drivers of the emergent longevity gap in order to study in a rigorous way the economic incentives and mechanisms that govern the dynamics. Calibrating the model to reflect US data over the time span 1960-2005, we assess the quantitative significance of the different channels. In addition, our numerical analysis allows us to study how biases in earnings growth and in the access to medical progress interact as drivers of the longevity gap. Thus, we are able to study the two channels in a unified way that takes our paper beyond the empirical approaches so far, which have mostly concentrated on examining a single channel.

To do so, we develop an overlapping generations model populated by heterogeneous agents subject to endogenous mortality. We model two groups of individuals who differ in their skills, e.g. due to differences in education. The resulting difference in labour productivity translates into differential earnings and earnings growth. In addition, skill-related differences in ability to use medical technology effectively lead to a differential impact of health care expenditure on survival chances. Individuals purchase a consumption good from which they derive utility over their life-course and health care with a view to affecting their survival prospects. Overall, individuals seek to maximize their life-cycle utility. The economy consists of two sectors, a medical sector providing health care and a production sector producing the consumption good. The relative price of health care is determined endogenously and depends on the sector-specific use of production factors and their general equilibrium prices.

We derive the age-specific individual demand for health care based on the value of life, the level of medical technology and the consumer price of health care. Given the income level as well as the effectiveness of medical care within each of the two groups, we are

[2] See Schröder et al. (2016) for a recent systematic review of the literature on the SES gradient in the access to treatment for coronary heart disease, highlighting effects of both income and education.

able to determine a baseline level of mortality inequality. We then study the impact of (i) skill-biased technological progress in the production sector, leading to a widening in the earnings gaps; and (ii) skill-biased access to advancements in the overall effectiveness of medical care in improving individual health to examine how these two forms of progress bear on disparities in the use of health care and on mortality. We pay particularly close attention to macroeconomic effects caused by differential productivity growth and medical progress on the price for medical care and its feedback on the individual demand for health care within the two groups. When studying the role of productivity growth, we follow Baumol's (1967) theory, according to which productivity gains in capital-intensive sectors do not only cause income growth but also lead to rising production costs in labor-intensive sectors, such as health care. Given that income growth disproportionately benefits high skilled inviduals, whereas the price for health care rises for all individuals, this may imply a widening gap in the access to health care. We explore the relevance of this channel in affecting mortality inequality.

We replicate in our model the increase over the time span 1960-2005 in the life expectancy gap by some 3.1 years between the 50 percent top earners (representing the skilled) and the 50 percent bottom earners (representing the unskilled) in the US, and find that about 16 percent of the increase are explained by skill-biased earnings growth, about 52 percent by skill-bias in the access to state-of-the-art medicine, whereas 33 percent of the increase are explained by the fact that the initial (1960) gap in earnings translates into a difference in health care spending which owing to medical progress leads to a widening gap in survival outcome. Thus, the skilled are able to expand their relative survival opportunities (i) due to a rising ability and propensity to spend on health care in the presence of skilled-biased earnings growth; (ii) due to their better access to state-of-the-art care for any given level of health care spending, an effect which is exarcerbated due to medical progress overall;[3] and (iii) due to a complementarity between income and medical progress such that their higher consumption of health care from the outset allows them to participate to an increasing extent in the benefits from medical advances. Finally, we find that while medical prices increase by a factor about 1.5 over the time span 1960-2005, this does not contribute to a widening in the longevity gap. However, it nevertheless implies that the unskilled forego about 25 percent of the potential increase in life expectancy (for a given price of health care) whereas the skilled forego only about 16 percent.

A number of recent papers address the income and education related inequality in health outcomes within formal life-cycle models. Capatina (2015) studies the role of different health risks over the life cycle across different strata of education. She does not, however, endogenise the consumption of health care. Prados (2013) studies the interrelationship between income and health inequality over the working life with a particular focus on the feedback from health on earnings. Ales et al. (2014) study the (social) efficiency of differences in health care spending and, depending on this, in longevity across individuals with different earnings potential. Ozkan (2015) studies the incentives for individuals from different income groups to invest in preventive and curative care in a model in which health shocks lead to a deterioration of a stock of health and higher mortality and finds that the subsidisation especially of preventive health care for the poor may yield significant welfare gains. Finally, Cole et al. (2018) study the impact of recent US reforms aimed at curbing health-realted discrimination within the labour and insurance markets on preventive behaviour and welfare when individuals differ in their health.

None of these works addresses the dynamics of the education/income gradient in mortality as a consequence of skill-biased productivity growth and skill-biased access to medical progress. Such an analysis is important, as it provides a sound theoretical basis for under-

[3] Intuitively, access to the state-of-the-art treatment for a given condition only matters once effective treatments have been developed. Thus, skill-related differences in access are reinforced over time with the advent of more and more effective treatments.

standing and assessing the transmission channels that underly the empirical findings on the impact of education and income on individuals' propensity to benefit from health care and medical progress. To our knowledge, the only other theoretical approach toward understanding the role of differential access to medical progress is Goldman and Lakdawalla (2005). Studying the comparative static properties of a static model of the demand for health care, they identify the greater demand for health care on the part of individuals with high socio economic status (conditional on medical need) as a key condition for a differential impact on longevity of productivity growth in the health care sector. This is because an increases in medical productivity, in their case modelled as decline in the price of health care, tends to boost the demand for health care by more for those with greater socio economic status. While the greater propensity to benefit from medical progress for those with high demand also plays a role in our model, the mechanism goes through the effectiveness of medical technology rather than the productivity of the health care sector. Indeed, in line with the empirical evidence the price in health care is increasing in our model rather than declining. More generally, our paper relates to an emerging literature on the role of medical progress within the macroeconomy (Suen 2009, Chandra and Skinner 2012, Fonseca et al. 2013, Jones 2016, Koijen et al. 2016, Schneider and Winkler 2016, Böhm et al. 2017, Frankovic et al. 2017, Frankovic and Kuhn 2018). Covering various aspects of medical progress, none of these works address its role as a driver of the emerging longevity gap.

The remainder of the paper is set out as follows. Section 2 introduces the model (Sections 2.1-2.4) and provides details on the solution (Sections 2.5 and 2.6); Section 3 introduces the calibration of the model (Section 3.1) and provides the results of our numerical analysis (Section 3.2); Section 4 concludes. Some mathematical derivations and details on the numerical simulation have been relegated to an Appendix (Section 5).

2 Model

We consider two groups of individuals who differ in their skill (education) level $i = s, u$, with s denoting the skilled and u denoting the unskilled, respectively. The differences in skills translate into (i) differential labour productivity and, thus, into differential earnings (as documented e.g. in Acemoglu and Autor 2011); and (ii) into differential ability to use medical technology/know-how effectively in order to improve health and survival chances (as documented e.g. in Glied and Lleras-Muney 2008, Avitabile et al. 2011, Lange 2011, Hernandez et al. 2018). Both groups are represented by overlapping generations of individuals who choose consumption and health care over their life-course. We should stress at this point that we are not interested in explaining the causality of income as opposed to education as drivers of inequality in health, nor any reverse causality, but rather in exploring the channels through which differences in education/skills translate into differences in individuals' ability to participate in the benefits from health care and medical progress.

2.1 Individual problem

Life-cycle utility of a representative from group $i = s, u$ who is born at $t_0 = t - a$ is given by[4]

$$\max_{c_i(\cdot),h_i(\cdot)} \int_0^\omega e^{-\rho a} u(c_i(a,t)) S_i(a,t) da, \tag{1}$$

where a and t denote age and time, respectively; where $u(\cdot)$, with $u_c > 0, u_{cc} < 0$, denotes the instantaneous utility function with the usual properties; where $c_i(\cdot)$ and $h_i(\cdot)$ denote consumption and health care, respectively; where ρ denotes the rate of time preference;

[4] Note that from the individual's perspective age and time progress simultaneously, following the identity $a \equiv t - t_0 \in [0, \omega]$ for $t \in [t_0, t_0 + \omega]$. Thus, we have $\int_0^\omega e^{-\rho a} u(c(a,t)) S(a,t) da = \int_0^\omega e^{-\rho a} u(c(a, t_0 + a)) S(a, t_0 + a) da = \int_{t_0}^{t_0+\omega} e^{-\rho t} u(c(t - t_0, t)) S(t - t_0, t) dt$.

where ω denotes the maximal attainable age; and where

$$S_i(a,t) = \exp\left[-\int_0^a \mu_i(\widehat{a},\widehat{t},h_i(\widehat{a},\widehat{t}),M_i\left(\widehat{t}\right))d\widehat{a}\right]$$

denotes the survival function with $\mu_i(\cdot)$ being the skill specific mortality rate. Mortality can be curbed by health care, $\mu_{ih} < 0$, $\mu_{ihh} > 0$, the effectiveness of which depends on the skill-dependent access to innovative health care $M_i\left(\widehat{t}\right)$, with $\mu_{iM} < 0$, $\mu_{ihM} \leq 0$. Intuitively, we would expect $M_u(t) \leq M_s(t)$, implying that unskilled individuals may suffer from restrictions in the access to the most effective health care. Following Chandra and Skinner (2012), Kuhn et al. (2015) and Frankovic et al. (2017) one can also interpret $S_i(a,t)$ as a measure of the stock of health at (a,t,i), which allows for a more general interpretation of the model including quality-of-life aspects of health. For the representative individual the assumption that health care can slow down but not reverse the decline of health over the life course is plausible and well in line with evidence on the gradual accumulation of health deficits over the life course (Rockwood and Mitnitski, 2007; Dalgaard and Strulik 2014).

The individual faces the following skill-specific state constraints:[5]

$$\begin{aligned}
\dot{S}_i(a,t) &= -\mu_i(a,t,h_i(a,t))S_i(a,t), && (2)\\
\dot{k}_i(a,t) &= r\left(t\right)k_i(a,t) + l_i(a)w_i(t) - c_i(a,t) - \phi_i(a,t)p_H(t)(h_i(a,t)+e_i(a,t))\\
&\quad -\tau_i(a,t) + \pi_i(a,t) + s(t), && (3)
\end{aligned}$$

with $S_i(0,t_0) = 1$, $S_i(\omega,t_0+\omega) = 0$ and $k_i(0,t) = k_i(\omega,t) = 0$ as boundary constraints.

[5]In the following, we will use the $\dot{()}$ notation to indicate both the derivative $\dot{x}\left(a,t\right) := x_a + x_t$ for life-cycle variables and the derivative $\dot{X}\left(t\right) := X_t$ for aggregate variables. Drawing again on the identity $t \equiv t_0 + a$ from the individual's perspective, it follows that $\dot{x}\left(a,t\right)$ collapses into a single dimension.

Survival is reduced over the life-course according to the force of mortality. The individual's stock of assets $k_i(a,t)$ (i) increases with the return on the current stock, where $r\left(t\right)$ denotes the interest rate at time t; (ii) increases with earnings $l_i(a)w_i(t)$, where $l_i(a)$ denotes the exogenous labour supply of an individual from group i at age a and where $w_i(t)$ denotes the skill-specific wage rate at time t; (iii) decreases with consumption, the price of consumption goods being normalized to one; (iv) decreases with private health expenditure, $\phi_i\left(a,t\right)p_H(t)(h_i(a,t)+e_i(a,t))$, where $p_H(t)$ denotes the price for health care, where $\phi_i\left(a,t\right)$ denotes an (a,t,i)-specific rate of coinsurance, and where the total consumption of health care amounts to the sum of elective health care $h_i(a,t)$ and emergency care $e_i(a,t)$, the latter not being subject to the individual's choice; (v) decreases with an (a,t,i)-specific tax, $\tau_i\left(a,t\right)$; (vi) increases with (a,t,i)-specific benefits $\pi_i\left(a,t\right)$; and (vii) increases with a lump-sum transfer $s(t)$ by which the government redistributes accidental bequests across the population. We follow Frankovic et al. (2017) and others by considering a setting without an annuity market.

Note that while the market-wide interest rate $r(t)$, the price for health care $p_H(t)$ and the lump-sum transfer $s(t)$ are identical for both skill groups, their wages are skill-specific, where we would typically expect $w_s(t) \geq w_u(t)$, reflecting higher productivity of the skilled. The co-insurance rate, tax-rate and pension benefits are also allowed to vary with the skill level.

Finally, we assume that emergency health care $e_i(a,t) = e(S_i(a,t))$, with $e_S(S_i(a,t)) < 0$, is a decreasing function of the survival of a type i representative to age a at time t. This reflects the notion that in situations of critical illness, as expressed by a low probability of survival as a proxy for the health state, individuals must incur expenditures $e_i(a,t)$ in order to survive without having a degree of choice. Note that the dependency of emergency care on survival also implies that health expenditures are particularly high close to the time of an individual's death (e.g. Zweifel et al. 1999). When chosing their individual level of elective health care, individuals internalize the effect on lower emergency health care expenditures operating through increased survival over the life-cycle.

2.2 Population

Let $N_i^c(a,t) = S_i(a,t)B(t-a)$ denote the size of the cohort of skill level $i = s, u$ that was born at time $t-a$ and is alive at age a at time t. By aggregating over age and skills we obtain the following expressions for population size, aggregate capital stock, aggregate effective labour supply, aggregate consumption (of final goods), aggregate (consumption of) health care, aggregate tax revenue and aggregate benefit payments:

$$\begin{aligned} N(t) &= \int_0^\omega \left[N_s^c(a,t) + N_u^c(a,t)\right] da, & (4)\\ K(t) &= \int_0^\omega \left[k_s(a,t)N_s^c(a,t) + k_u(a,t)N_u^c(a,t)\right] da, & (5)\\ L(t) &= \int_0^\omega \left[l_s(a)N_s^c(a,t) + l_u(a)N_u^c(a,t)\right] da, & (6)\\ C(t) &= \int_0^\omega \left[c_s(a,t)N_s^c(a,t) + c_u(a,t)N_u^c(a,t)\right] da, & (7)\\ H(t) &= \int_0^\omega \left[(h_s(a,t) + e_s(a,t))N_s^c(a,t) + (h_u(a,t) + e_u(a,t))N_u^c(a,t)\right] da, & (8)\\ \Upsilon(t) &= \int_0^\omega \left[\tau_s(a,t)N_s^c(a,t) + \tau_u(a,t)N_u^c(a,t)\right] da, & (9)\\ \Pi(t) &= \int_0^\omega \left[\pi_s(a,t)N_s^c(a,t) + \pi_u(a,t)N_u^c(a,t)\right]. & (10) \end{aligned}$$

We assume that births grow exogenously at the rate ν such that

$$B_i(t) = B^0 \exp^{\nu t}, \quad B^0 > 0. \tag{11}$$

2.3 Production

The economy consists of a manufacturing sector and a health care sector. In the manufacturing sector a final good is produced by employment of capital, $K_Y(t)$, as well as skilled and unskilled labor, $L_s^Y(t)$ and $L_u^Y(t)$, respectively. Assuming a neo-classical Cobb-Douglas production function, we can write profit in the manufacturing sector as

$$V_Y = Y(K_Y, A_s^Y L_s^Y, A_u^Y L_u^Y) - w_s L_s^Y - w_u L_u^Y - [\delta + r]\, K_Y, \tag{12}$$

with

$$Y(K_Y, A_s^Y L_s^Y, A_u^Y L_u^Y) = K_Y^\alpha (A_s^Y L_s^Y + A_u^Y L_u^Y)^{(1-\alpha)}. \tag{13}$$

Here, $\delta \geq 0$ denotes the rate of capital depreciation, whereas A_s^Y and A_u^Y denote the productivity of skilled and unskilled labour in final goods production, respectively. Intuitively, and in line with evidence on the wage patterns (e.g. Acemoglu and Autor 2011), we have $A_s^Y \geq A_u^Y$. Indeed, we will assume later on that in line with skill-biased technical progress we have that $\dot{A}_s^Y > \dot{A}_u^Y$.[6]

In analogy to final goods production, we assume that health care is produced by employment of capital, $K_H(t)$, as well as skilled and unskilled labor, $L_s^H(t)$ and $L_u^H(t)$, respectively, with profits given by

$$V_H = p_H F(K_H, A_s^H L_s^H, A_u^H L_u^H) - w_s L_s - w_u L_u - [\delta + r]\, K_H \tag{14}$$

[6] The Cobb-Douglas specification in (13) amounts to the special case of the typical CES formulation with an infinite elasticity of substitution between skilled and unskilled labour (see e.g. Acemoglu and Autor 2011). The focus of the present analysis being on the implications of differential earnings growth for health care rather than the underlying employment changes, we believe this simplification does not greatly bear on our results.

where p_H is the price for health care, and where

$$F(K_H, A_s^H L_s^H, A_u^H L_u^H) = K_H^{\beta}(A_s^H L_s^H + A_u^H L_u^H)^{(1-\beta)}. \tag{15}$$

Note that $V_Y = V_H = 0$ in a perfectly competitive equilibrium.

We allow the factor elasticities in the health care sector to differ from those in final goods production, where in line with evidence in Acemoglu and Guerrieri (2008) we assume $\beta < \alpha$, implying that the health care sector is less capital intensive. We also allow for cross-sectoral differences in the levels of labour productivity $A_s^H \lesseqgtr A_s^Y$ and $A_u^H \lesseqgtr A_s^Y$. For a competitive equilibrium with an interior solution to the labour allocation, such that $L_i^j > 0$ for all $i = s, u$ and $j = Y, H$, we need to assume that the relationship

$$\frac{A_s^H}{A_u^H} \equiv \frac{A_s^Y}{A_u^Y} \tag{16}$$

holds at all times (see Appendix 5.2). This implies, in particular that the productivity ratio between the skilled and unskilled is independent of the sector and that while productivity growth may differ across sectors and skill groups such that e.g. $\dot{A}_s^Y > \dot{A}_s^H$ and $\dot{A}_s^Y > \dot{A}_u^Y$, these differences must satisfy the proportionality requirement:

$$\frac{\dot{A}_s^Y}{A_s^Y} - \frac{\dot{A}_u^Y}{A_u^Y} \equiv \frac{\dot{A}_s^H}{A_s^H} - \frac{\dot{A}_u^H}{A_u^H}.$$

2.4 Health Insurance, Social Security and Accidental Bequests

We assume that the government and/or a third-party payer (e.g. a health insurer) raise taxes (or contribution rates, e.g. insurance premiums) for the purpose of co-financing health care at the rate $1-\phi_i(a,t)$ and paying out transfer payments $\pi_i(a,t)$. In particular,

$\pi_i\,(a,t)$ may relate to pension benefits, implying that

$$\pi_i\,(a,t) = \begin{cases} 0 \Leftrightarrow a < a_R \\ \pi_i(t) \geq 0 \Leftrightarrow a \geq a_R \end{cases}$$

with $\pi_i(t)$ a uniform but group-specific pension benefit at time t and a_R the retirement age. In such a setting we also have

$$l_i(a) = \begin{cases} l_i(a) \geq 0 \Leftrightarrow a < a_R \\ 0 \Leftrightarrow a \geq a_R \end{cases}.$$

Likewise, $\tau_i\,(a,t)$ are age- and group-specific taxes set at levels that ensure the government's and private health insurer's budget balance

$$\begin{aligned} \Upsilon\,(t) &= p_H\,(t) \int_0^{\omega} \left\{ \begin{array}{c} [1-\phi_s\,(a,t)]\,[h_s(a,t)+e_s(a,t)]\,N_s^c(a,t) \\ +\,[1-\phi_u\,(a,t)]\,[h_u(a,t)+e_u(a,t)]\,N_u^c(a,t) \end{array} \right\} da \\ &\quad +\Pi\,(t) + G\,(t)\,, \end{aligned}$$

where $\Upsilon\,(t)$ and $\Pi\,(t)$ are defined in (9) and (10), respectively, and where $G\,(t) \geq 0$ denotes government expenditure on activities that are exogenous to the model. Further details on the modeling of health insurance and social insurance are provided in Section.3.1 on the calibration of the model.

Finally, we assume that accidental bequests are redistributed in a lump-sum fashion across the population, such that each individual who is alive at t receives a transfer[7]

$$s(t) = \frac{\int_0^{\omega} [\mu_s(a,t)k_s(a,t)N_s^c(a,t) + \mu_u(a,t)k_u(a,t)N_u^c(a,t)]\,da}{\int_0^{\omega} [N_s^c(a,t) + N_u^c(a,t)]\,da} \tag{17}$$

[7]In order to ease on notation, we will subsequently refer to the shortcut $\mu_i(a,t)$ for $\mu_i(a,h_i(a,t),M_i(t))$.

Note that the redistribution of accidental bequests across income groups implies a certain levelling of divergences in wealth. We aim for this specification as the accidental bequests under consideration likely are a poor proxy for systematic differences in inheritances as drivers of a widening inequality in wealth.[8] For robustness, we have also run the model under the assumption that accidental bequests are redistributed within skill groups but have found little quantitative difference.

2.5 Individual Life-Cycle Optimum

In Appendix 5.1 we show that the solution to the individual life-cycle problem is given by the following set of conditions for individuals from group $i = s, u$:

$$\begin{aligned} & \frac{u_c\left(c_i\left(a,t\right)\right)}{\exp\left\{-\int_a^{\widehat{a}}\left[\rho+\mu_i\left(\widehat{\widehat{a}},t+\widehat{\widehat{a}}-a\right)\right]d\widehat{\widehat{a}}\right\}u_c\left(c_i\left(\widehat{a},t+\widehat{a}-a\right)\right)} \\ = \quad & \exp\left[\int_a^{\widehat{a}} r\left(t+\widehat{\widehat{a}}-a\right)d\widehat{\widehat{a}}\right] \end{aligned} \tag{18}$$

describing the optimal pattern of consumption, and

$$\psi_i\left(a,t\right) = \frac{-\phi_i\left(a,t\right)p_H\left(t\right)}{\mu_{ih}\left(a,t\right)} \quad \forall\left(a,t,i\right) \tag{19}$$

describing the optimal choice of elective health care. Here, $\psi_i\left(a,t\right)$ denotes the (extended) private value of life, i.e. the individual's willingness to pay for surviving through $\left(a,t\right)$.

Condition (18) is the well-known Euler equation, requiring that the marginal rate of intertemporal substitution between consumption at any two ages/years (a,t) and $(\widehat{a}, t+\widehat{a}-a)$ equals the compound interest. Note that in the absence of annuities, the uninsured mortality risk can be interpreted as an additional factor of discounting, implying an effective

[8] While the skilled are prone to hold greater wealth within each age group, they also face lower mortality up to the highest age classes in which most of the wealth has been spent down. Thus, it is not even clear a priori whether accidental bequests from the skilled may not be lower than those from the unskilled.

discount rate $\rho + \mu_i(a,t)$ at any (a,t). Rising mortality then implies a downward drag on consumption toward the end of life. Moreover, differences in mortality across the skill groups, translate into different patterns of discounting. More specifically, if the unskilled face a greater mortality risk, i.e. if $\mu_u > \mu_s$, then they are more prone to consume early on in life and save less.

Condition (19) requires that at each (a,t,i) the private value of life $\psi_i(a,t)$, equals the price of survival, $-\phi_i(a,t)\, p_H(t) / \mu_{ih}(a,t)$. Here, the consumer price for health care, $\phi_i(a,t)\, p_H(t)$, is converted into a price of survival by weighting with the number of units of health care required for a unit reduction in mortality, $[\mu_{ih}(a,t)]^{-1}$.

The extended value of life is given by

$$\psi_i(a,t) = \int_a^{\omega} \left[\frac{u_i(\widehat{a}, t+\widehat{a}-a)}{u_{ic}(\widehat{a}, t+\widehat{a}-a)} - \phi_i p_H e_{iS} S_i(\widehat{a}, t+\widehat{a}-a) \right] \exp\left[-\int_a^{\widehat{a}} r(t+\hat{\hat{a}}-a) d\widehat{\widehat{a}} \right] d\widehat{a} \quad , \tag{20}$$

amounting to the discounted stream of consumer surplus, $u_i(\cdot)/u_{ic}(\cdot)$ over the expected remaining life-course $[a,\omega]$. Additionally, the term $\phi_i p_H e_{iS} S_i(\widehat{a}, t+\widehat{a}-a)$ (with $e_{iS} < 0$) measures the expected cost saving with respect to emergency care expenditures at future age/time $(\widehat{a}, t+\widehat{a}-a)$ from higher survival at (a,t).[9] It is readily checked that the value of life at each (a,t) increases (i) with the level of the individual's consumption and, thus, the individual's income, (ii) with the distribution of consumption over the remaining life-course, and (iii) with the savings on future emergency health care. Focusing on the consumption-related parts (i) and (ii), the value of life tends to be higher at high ages for skilled individuals as long as they are facing lower mortality rates, $\mu_s < \mu_u$. According to the functional specification (??), the extent to which this is true depends (i) on the extent

[9] The value of life as we calculate it here differs from the typical representation as e.g. in Shepard and Zeckhauser (1984), Rosen (1988), or Murphy and Topel (2006) in as far as (i) the discount factor does not include the mortality rate; (ii) the value of life does not include the current change to the individual's wealth, $lw - c - h - \tau + \pi + s$; and (iii) the additional term relating to savings on future emergency care. While (iii) is specific to the model set up we are considering, (ii) and (iii) are owing to the absence of an annuity market.

to which they use their higher income for the purchase of additional health care, and (ii) on their relative advantage in having access to the most effective form of medical medical care, as measured by, $M_s(t) > M_u(t)$. Thus, one would expect that $\psi_s(a,t) > \psi_u(a,t)$ both on count of higher consumption levels and on count of a lower mortality risk, leading to a more even distribution of consumption over the life-course.

The price of survival (a,t), in turn, decreases (i) with health insurance coverage, $1 - \phi_i(a,t)$, at (a,t), and (ii) with the state of the medical technology, given that the latter raises the effectiveness of health care, $\mu_{ih}(a,t) < 0$. Greater effectiveness in the use of health care for the skilled, $\mu_{sh}(a,t) < \mu_{uh}(a,t)$ would ceteris paribus imply a lower effective price for survival. Whether or not the skilled as opposed to the unskilled are facing a greater extent of insurance coverage, such that $\phi_s(a,t) < \phi_u(a,t)$ is a matter of institutional design. Empirical evidence for the US as presented in Capatina (2015) and summarized in Table 1 further on below, suggests that the skilled are enjoying moderately higher levels of insurance coverage. Thus, for this reason, too, it is likely that the skilled are facing a lower price of survival. Facing both a higher benefit from survival and a lower price for it, the skilled are prone to spend more on elective health care, i.e. $h_s(a,t) > h_u(a,t)$. Note, however, that their lower survival, $S_u(a,t) < S_s(a,t)$, would imply that the unskilled face higher spending on emergency care, $e_u(a,t) > e_s(a,t)$, implying similar or even greater total outlays.

2.6 General equilibrium

Perfectly competitive firms in the two sectors $j = Y, H$ choose capital $K_j(t)$ and the two types of labour $L_i^j(t)$ with $i = s, u$ so as to maximize their respective period profit (12) and (14). The six first-order conditions determine the six (sector-specific) factor demand functions, depending on the set of prices $\{r(t), w_s(t), w_u(t), p_H(t)\}$.[10] Likewise, we obtain the age- and skill-specific demand for consumption goods $c_i(a,t)$ and health care $h_i(a,t)$ from the sets of first-order conditions (18) and (19) of the individual life-cycle problem. The age profiles of individual wealth $k_i(a,t)$ then follows implicitly from the life-cycle budget constraint (3). Aggregating across the age-skill-groups alive at each point in time t according to (5)-(8) gives us the aggregate supply of capital $K(t)$ and labour $L(t)$, as well as the aggregate demand for consumption $C(t)$ and health care $H(t)$. The general equilibrium characterization of the small open economy is completed by the set of six market clearing conditions

$$
\begin{aligned}
L_s^H(t) + L_s^Y(t) &= L_s(t) && (21)\\
L_u^H(t) + L_u^Y(t) &= L_u(t) && (22)\\
K_Y(t) + K_H(t) &= K(t) && (23)\\
Y(K_Y(t), A_s^Y(t)L_s^Y(t), A_u^Y(t)L_u^Y(t)) &= C(t) + \dot{K}(t) + \delta K(t) && (24)\\
F(A_H(t), A_s^H(t)L_s^H(t), A_u^H(t)L_u^H(t)) &= H(t) && (25)
\end{aligned}
$$

corresponding to the skill-specific labour markets, the capital market, the market for final goods and the market for health care, respectively. From these, we then obtain a set of equilibrium prices $\{r^*(t), w_s^*(t), w_u^*(t), p_H^*(t)\}$ and the level of net capital accumulation $\dot{K}(t)$. Appendix 5.2 provides a more detailed characterization based on the Cobb-Douglas production functions specified in (13), and (15), respectively.

[10] With appropriate Inada conditions on the production functions and given assumption (16), we always have an interior allocation with $L_i^H(t) = L(t) - L_i^Y(t) \in (0, L_i(t))$ for $i = s, u$ and $K_H(t) = K(t) - K_Y(t) \in (0, K(t))$.

3 Numerical Analysis

3.1 Calibration strategy

In the following, we solve the model outlined in the previous section by means of a numerical simulation. In doing so we calibrate the model to reflect the development of the US economy over the 50-year time span 1960-2010, capturing the evolution of income and life-expectancy among rich and poor individuals as well as the growth of average health care expenditures, medical technology and the price for medical care.[11] In order to study the various drivers of differential longevity growth, we first introduce exogenously trended group-specific labor productivity. Productivity of skilled labor grows at a higher-rate than productivity of unskilled labor. Productivity growth rates are thus chosen such that the skilled (unskilled) group's per-capita yearly income matches the evolution of mean income among the top (bottom) 50% of the income distribution as found in the data. We then apply average federal tax-rates such that we obtain realistic after-tax income evolution in each group. Hence, our model incorporates the increasing income inequality in the US over the last decades as driven by skill-biased technological change.

Second we introduce exogenous medical progress that increases the effectiveness of medical care in our model economy. Here, we assume for the unskilled relative to the skilled a lag of 11 years in the access to the state-of-the art medical technology. This lag increases the life-expectancy gap between the skill groups to a realistic level and contributes to a widening of the gap over time.

Third, we assume slower productivity growth in the health care sector as opposed to final goods production. In line with Baumol (1967), this implies that the health care sector absorbs an increasing share of labour, while at the same time the price of health

[11] The model will not be estimated using individual-level data, an approach that would overburden the solving algorithm used here, see Frankovic et al. (2017).

care increases endogenously.

Due to the diverging incomes between the skill groups, due to differential access to medical progress, and due to the increase of the price of health care, life-expectancy among the skilled/rich and unskilled/poor diverges endogenously in the model. The diverging life-expectancies match quite well recent data on the development of life-expectancy by income strata as provided by Chetty et al. (2016). The model thus offers an economic rationale for the trends observed. While we cannot claim that the progression of the life-expectancy gap can be explained by those three factors alone, we can offer a decomposition into the relative strength of each of these channels as part of their aggregate effect. Further details on the calibration and data we employ are provided in the following.

Income

Data on the market income evolution of rich and poor in our model is based on the evolution of mean income within the top and bottom 50% of the households in the US as provided by the United States Census Bureau, Table H-3.[12] Since after-tax income is the decisive variable in the spending decisions of households, however, we also match the after-tax income evolution of the two groups in our model with the respective trends for the top and bottom 50% of households. For this purpose, we employ data from Congressional Budget Office (2016), which provides mean market income and after-tax income of households in five quintiles for the year 2013. Since the same publication shows, that market-income and after-tax income inequality among US households has not diverged to any great extent over the last decades, we use the 2013 ratio of after-tax to market-income of the top and bottom 50% to obtain average tax rates for each group, namely 22.7% for the top income group and

[12]The Table H-3 "Mean Household Income Received by Each Fifth and Top 5 Percent" is available at https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-income-households.html. We approximate the top (bottom) 50 % mean income by the average of mean incomes among the top (bottom) three fifths, where the third fifth receives only half the weight in each of our two groups.

8.7% for the bottom income group. We then introduce these figures as exogenous labour income tax rates on each group separately and obtain a realistic evolution of after-tax income inequality in the model. For the lack of better data, we assume that the age-specific labour supply does not differ between skill groups and is constant over the whole time horizon (while wages increase). We then proxy the effective labour supply of both age groups by an age-specific income schedule taken from Frankovic et al. (2017).

Life-expectancy, mortality, medical progress and emergency expenditure

Average life-expectancy among individuals from the top and bottom 50% income groups are taken from Chetty et al. (2016).[13] Unfortunately, the data series is limited to the years 2001 through 2014. However, there is evidence, that the life-expectancy differential between the top and bottom half of the income distribution was close to zero around the middle of the 20th century (Congressional Research Office, 2017). Thus, we base our calibration on the assumption that the group-specific life-expectancy diverge from the same starting point in 1950.

The force of mortality $\mu_i(a,t) = \mu\left(h_i\left(a,t\right), M_i\left(t\right)\right)$ is endogenously determined in the model and depends on health care, $h_i\left(a,t\right)$, as a decision variable, and on the access to the newest medical technology, $M_i(t)$. Following Frankovic and Kuhn (2018), we formulate

$$\mu_i(a,t) = \eta(a)\left(h_i(a,t)\right)^{\kappa M_i(t)}, \tag{26}$$

where $\eta(a) > 0$ and $\kappa < 0$ reflect the age-specific effectiveness of health care. We choose $\kappa = 0.1$ such that the age-specific elasticities of mortality with respect to health care utilization, given by $M_i(t)\kappa$, are in the range of -0.1 to -0.25 for both education groups,

[13] We use Table 2 from the accompanying website at https://healthinequality.org/data/. Life-expectancy is given disaggregated to sex and hundred income percentiles. We aggregate the data to obtain average life-expectancy among the top and bottom 50% of income distribution.

which is in line with average estimated elasticities as reported in Hall and Jones (2007). The term $\eta(a)$ is established in Frankovic and Kuhn (2018) for a representative individual and used here in the same fashion. We assume additionally that medical technology available to the unskilled lags behind the one that is available to the skilled - or equivalently is used at a lower effectiveness. We choose a lag of 11 years which increases the life-expectancy gap to a magnitude in line with the data.[14] Thus, we set $M_u(t) = M_s(t-11)$. Assuming $M_s(t)$ to reflect the state-of-the-art medical technology, we impose a growth trend on $M_s(t)$ that together with the lagged $M_u(t)$ is consistent with the growth of aggregate health expenditure, $H(t)$.

Finally, we assume that emergency health care follows the specification

$$e_i(a,t) = \xi_1 (S_i(a,t))^{\xi_2}, \tag{27}$$

with $\xi_1 \geq 0, -1 < \xi_2 < 0$. Specifically, we set $\xi_1 = 0.3$ and $\xi_2 = -0.1$ in our calibration.

Utility

We assume instantaneous utility to be given by

$$u(a,t) = b + \frac{c(a,t)^{1-\sigma}}{1-\sigma},$$

where we choose the inverse of the elasticity of intertemporal substitution to be $\sigma = 1.1$ which is within the range of the empirically consistent values suggested by Chetty (2006).[15]

[14] Lags by socio-economic status in the diffusion/uptake of state-of-the art medical procedures have been reported for a number of conditions and health care settings (e.g. Skinner and Zhou 2004, Korda et al. 2011, Wang et al. 2012, Hagen et al. 2015, Clouston et al. 2017) with some notable exceptions (Goldman and Smith 2005). Most of these studies find that these lags translate into mortality differences, again with some exceptions (Hagen et al. 2015).

[15] Note that Hall and Jones' (2007) most preferred value for the inverse of the elasticity of intertemporal substitution is $\sigma = 2$. Presumably this is because the higher income elasticity of health care thus implied is necessary to explain the growing health share on the basis of income growth alone. As we are accounting medical progress as additional driver of spending growth, our modelling implies a lower income elasticity.

Setting $b = 10$ then guarantees that $u(a,t) \geq 0$ throughout and generates an average VOL that lies within the range of plausible estimates, as suggested in Viscusi and Aldy (2003).[16] Moreover, we assume a rate of time preference $\rho = 0.02$.

Finally, following Frankovic and Kuhn (2008) we impose a minimum consumption level equal to the social security benefit (of the bottom 50%) at a given point in time. We do so in order to avoid negative asset holdings at old age, as would otherwise result from ex-ante optimization.[17] Given that retirees cannot usually loan against future pension income and given that individuals are downspending their assets in old age (as they do within our model) the minimum consumption constraint is plausible.

Insurance, Social Security and Taxes

We follow Capatina (2015) with respect to the calibration of insurance coverage. She reports average co-payment shares for the two time periods 1996-2002 and 2003-2010 of college and non-college educated individuals which we take as proxy for the skilled and unskilled population in our model. Table 1 provides an overview of average health expenditure shares payed for by various insurance programs. A Medicare tax is levied as a payroll tax $\tau_{MC}(t)$ and set at each point in time such that Medicare co-payments at a uniform rate of $\phi_{MC}(a,t) = \phi_{MC} = 0.5$ are fully financed:

$$\tau_{MC}(t)w(t)L(t) = \int_{a_R}^{\omega} \left\{ \begin{array}{c} (1-\phi_{MC})\, p_H(t) \left[h_s(a,t) + e_s(a,t)\right] N_s^c(a,t) \\ +\,(1-\phi_{MC})\, p_H(t) \left[h_u(a,t) + e_u(a,t)\right] N_u^c(a,t) \end{array} \right\} da.$$

[16] The model yields a value of life of approx. 4 million USD for skilled and 1.5 million USD for unskilled individuals.

[17] Individuals choose old-age consumption at the beginning of their life, attaching a low probability to reaching very high ages. Consumption allocated to these ages (in the absence of a minimum consumption level) is thus very low and can fall below the social security income, such that it is optimal to pay back debt (accumulated to finance consumption at earlier ages) at very high ages with excess social security income.

Table 1: Insurance share of health expenditures

	Top 50%		Bottom 50%	
	1996-2002	2003-2010	1996-2002	2003-2010
Employer-based Insurance, during working life	0.651	0.637	0.588	0.546
Employer-based Insurance, during retirement	0.141	0.126	0.111	0.093
Medicare	0.5	0.5	0.5	0.5
Total Retirement	0.641	0.626	0.611	0.593

Private health insurance is paid for by insurance premiums equalling the expected health expenditures financed out of the private insurance, such that $\tau_i^P(a,t) = \left[1-\phi_i^P(a,t)\right] p_H(t)\left[h_i^*(a,t)+e_i^*(a,$ with $h_i^*(a,t)+e_i^*(a,t)$ denoting the equilibrium level of health expenditures for (a,t,i).

The revenue from the labor income tax $\tau_s^{IT}(t)w_s(t)L_s(t)+\tau_u^{IT}(t)w_u(t)L_u(t) = G(t)$, with $\tau_s^{IT}(t) = 0.227$ and $\tau_u^{IT}(t) = 0.087$, is used to finance government expenditures for exogenous activities $G(t) > 0$ that do not enter the individuals' budget constraint or utility function.

Individuals aged 65 or higher receive Social Security (SS) benefits financed by a payroll-tax levied on working individuals. We use data from the EBRI Databook on Employee Benefits[18] that report average SS income for five income quintiles for those aged 65 and higher from 1976 to 2012. Out of these we construct average SS income for the top and bottom income group following the same method as for market income. The data indicates that SS income for the bottom 50% has increased from 6400 (2012 constant) USD in 1976 to 9400 USD in 2012, whereas SS benefits for the top 50% have risen from 13600 USD to 14650 USD. In the model, total social security outlays are fully financed by a payroll tax rate levied uniformly on all workers at a given point in time. The endogenous payroll tax then amounts to 5.2% in 1975 and 8.6% in 2015.

[18]The complete Databook is available at https://www.ebri.org/publications/books/index.cfm?fa=databook. The data we use is provided in chapter 3.

Production Technology and Productivity Growth

Following Acemoglu and Guerrieri (2008), we set the capital share in final goods production and in the health care sector to $\alpha = 0.33$ and $\beta = 0.2$, respectively. Productivity growth among the skilled and unskilled is then chosen to match the evolution of the top and bottom incomes as described above. Specifically,we assume $\dot{A}_s^Y/A_s^Y = 0.014$ and $\dot{A}_u^Y/A_u^Y = 0.0045$. Productivity growth in the health care sector is assumed to be at $\dot{A}_s^H/A_s^H = -0.01$ and $\dot{A}_u^H/A_u^H = -0.0195$, such that p_H rises over time in accordance with data by the Bureau of Economic Analysis on the growth of medical prices relative to the overall CPI.[19] The interest rate is endogenously determined and evaluates at $r = 0.041$ in 1975 and $r = 0.033$ in 2015. The decline in the interest rate is due to population aging and a subsequent increase in average savings across the population.

Demography

Individuals enter the model economy at age 20 and can reach a maximum age of 100 with model time progressing in single years.[20] In our model, a "birth" at age 20 implies a maximum age $\omega = 80$. Population dynamics are partly endogenous due to mortality that is determined within the model and partly exogenous due to a growth of "births" at the fixed rate $\nu = 0.015$. Hence, the size of the skilled and unskilled group does not change over time and the overall population grows at a constant rate. This assumption is reflecting our choice of the skilled (unskilled) group to represent the top (bottom) 50% of the income distribution at each point in time. While this obviously amounts to an approximation of unobserved skills (or education) through income, we believe this to be legitimate in the light of observational equivalence in our data. We should also stress that we understand

[19] Note that negative productivity growth in the health care sector, as measured in terms of non-quality adjusted output, is consistent with the empirical evidence from a number of recent studies for the US (Sheiner and Malinovskaya 2016).

[20] We follow the bulk of the literature and neglect life-cycle decisions during childhood.

skilled/rich and unskilled/poor individuals to be representatives of their respective groups. Thus, we cannot - and for reasons of modeling clarity - do not wish to model the transition of individuals between the high and low income groups.

Overview of Functional Forms and Parameters

Table 2 summarises the most important parameters we are employing.

Parameter & Functional Forms	Description
$\omega = 80$	life span
$t_0 = 1950$	entry time of focal cohort
$\rho = 0.02$	pure rate of time preference
$\sigma = 1.1$	inverse elasticity of intertemporal substitution
$a_R = 65$	mandatory retirement age
$\delta = 0.05$	rate of depreciation
$\alpha = 0.33$	elasticity of capital in Y
$\beta = 0.2$	elasticity of capital in F
$\xi_1 = 0.3$	scale of emergency health care function
$\xi_2 = -0.1$	exponent in emergency health care function

Table 2: Model parameters

3.2 Results

In the following, we will present five sets of results. To begin with, the benchmark scenario in Section 3.2.1 describes the development of the economy and the resulting inequality in longevity over the time span 1960-2015. Set against this, we then study four counterfactual scenarios. (i) No skill-bias in productivity change and wage growth (Section 3.2.2): Here we consider a set-up in which the income of the skilled and unskilled follow the same growth trend whereas skill-biased medical progress follows the benchmark trend; (ii) No medical price inflation (Section 3.2.3): Here,we assume counterfactually the price for medical care to be fixed with skill-biased technical change and skill-biased medical change following their benchmark trends; (iii) no skill-bias in medical progress (Section 3.2.4): we study the absence of a lag in the access of the unskilled to medical innovations with skill-biased wage growth following the benchmark trend. (iv) no skill-bias in both productivity growth and medical progress (Section 3.3): Here, we assume the absence of skill-bias in both dimensions of technical and medical progress, while assuming the persistence of initial income inequality. We employ this "double" counterfactual for a decomposition analysis. in order to identify the individual contributions of skill-biased wage growth and skill-bias in the access to medical progress.

3.2.1 Benchmark

As is well known, the US have experienced more than half of a decade of growing earnings inequality. In our benchmark, we trace this development over the time span 1960-2015 for the after-tax earnings of the top 50% group as opposed to the bottom 50% group. In terminology of our model, we understand these two groups to be the "skilled" with high earnings as opposed to the "unskilled" with low earnings. Figure 1 plots differential earnings growth in our model against the data. Recall that earnings growth itself reflects the exogenous trends in the growth rates of the skill-specific productivity parameters A_s and A_u.

As Baumol (1967) shows, lagging productivity growth in the health care sector as opposed to final goods production leads to the reallocation of labour into the more labour intensive health care sector as well as to an increase in the wage rate(s). In combination, these effects drive up the price of health care, reflecting the increasing relative cost of producing health care (Figure 2, left panel).[21] Over the time span 1980-2000, medical

[21]See also Acemoglu and Guerrieri (2008) for a thorough analytical treatment of the underlying mechanisms as well as Frankovic et al. (2017) for a discussion how medical progress may lead to similar allocational impacts.

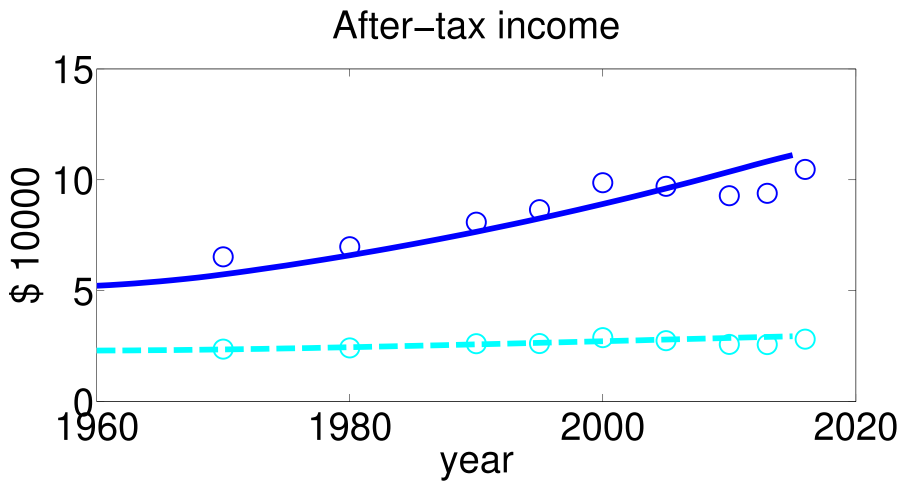

Figure 1: Evolution of after-tax wages for the top 50% (blue, solid) and the bottom 50% (cyan, dashed); Circles denote after-tax mean income of the top and bottom 50% as reported by the US census office.

prices have risen 1.6 times faster than the overall CPI according to the Bureau of Economic Analysis. This compares quite well with the 1.5-fold increase in p_H over the same time period in the benchmark economy. Furthermore, we assume medical technology to grow exponentially in a way that the increase in skill-specific life-expectancy in the model matches the data (Figure 2, right panel).

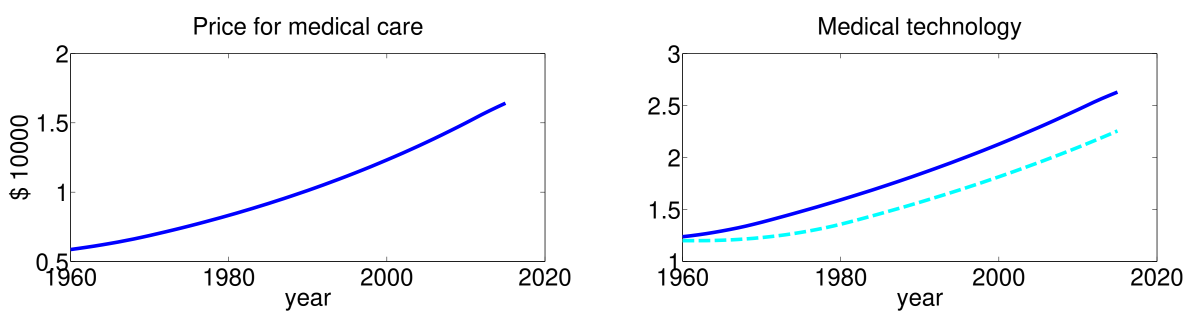

Figure 2: Evolution of the price for medical care $p_H(t)$ and the level of medical technology for the skilled ($M_s(t)$: blue, solid) and for the unskilled ($M_u(t)$: cyan, dashed).

Due to differential income growth, the increase in the price of health care and the differential access to rising medical technology, the life-expectancy of the top and bottom 50% earners diverges over time as can be seen in Figure 3.

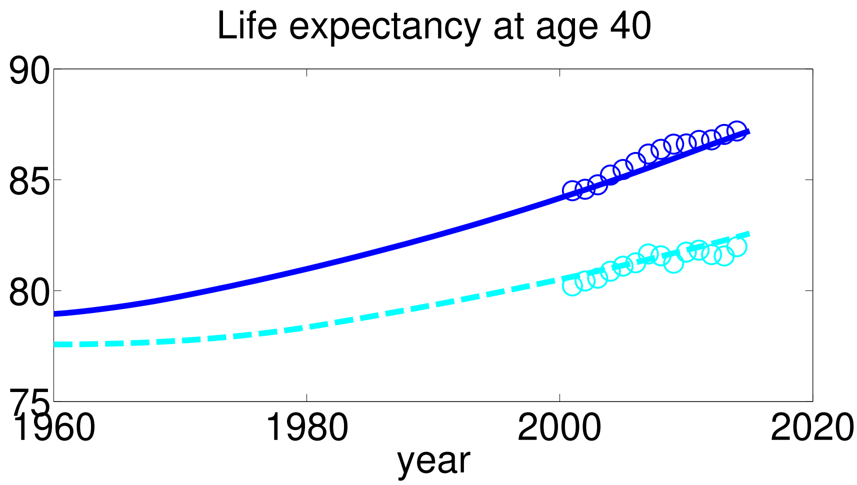

Figure 3: Evolution of life-expectancy for skilled (blue, solid) and unskilled (cyan, dashed)

While life expectancy increases by some 8.2 years from 78.9 in 1960 to 87.1 in 2015 for the high skilled top earners it increases by only 5.0 years from 77.7 to 82.7 for the low skilled. As can be seen from Figure 4 one factor underlying the growing life expectancy gap is the gradual divergence of health expenditures with the skilled spending at increasing rates. Note that this is well in line with the complementarity between income growth and medical progress as drivers of health care expenditure growth as evidenced in Fonseca et al. (2013) and Frankovic and Kuhn (2018).[22]

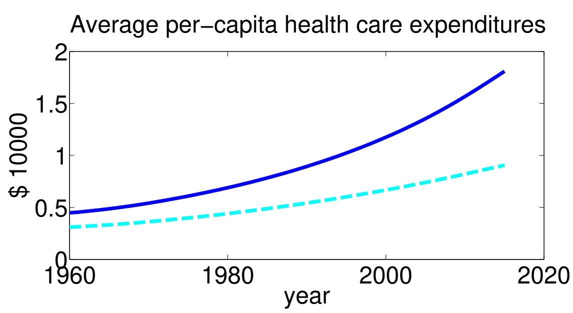

Figure 4: Average health care expenditures for skilled (blue, solid) and unskilled (cyan, dashed)

[22]It is also consistent with health care being a luxury good, as in Hall and Jones (2007). Notably, however, the complementarity between medical progress and income growth will lead to expanding health expenditure growth even for an income elasticity of health care spending below 1.

3.2.2 Counterfactual I: No skill-bias in earnings growth

In the following subsections the benchmark run will be represented by blue solid graphs, whereas the respective counterfactual experiments will be represented by green, dashed graphs. As a first counterfactual we consider a set-up where from 1960 onwards there is no skill bias in earnings growth, in the sense of the rate of earnings growth for the unskilled matching that for the skilled. What remains is the initial earnings gap, and medical progress continues to be biased toward the skilled as it is in the benchmark scenario. As can be seen in Figure 5, the life-expectancy of the unskilled now grows at a faster rate as opposed to the benchmark.

Figure 5: Evolution of earnings and life expectancy: Benchmark (blue, solid) and counterfactual I where earnings grow at same rate (green, dashed)

This is because higher growth of their income allows the unskilled to increase their health care spending at a higher rate relative to the benchmark (see bottom two lines in Figure 6), while the increase in health care expenditures among the skilled remains unchanged with respect to the benchmark (see top two (overlapping) lines in the same figure). Note, however, that for two reasons the unskilled continue to spend less on health care than the skilled: They continue to suffer from the initial earnings gap and they continue to have a lower propensity to spend owing to the fact that the care they buy is of lower effectiveness. One notable observation is the weakness of general impacts on earnings, health care sepnding and life expectancy of the skilled: Although the higher productivity growth for the unskilled in the counterfactual leads to a stronger growth of effective labour supply, this does not lead to a sizeable reduction in the earnings growth for the skilled. One reason for this is the increase in overall capital accumulation that is paralleling the increase in labour supply, leading to unchanged earnings growth for the skilled.

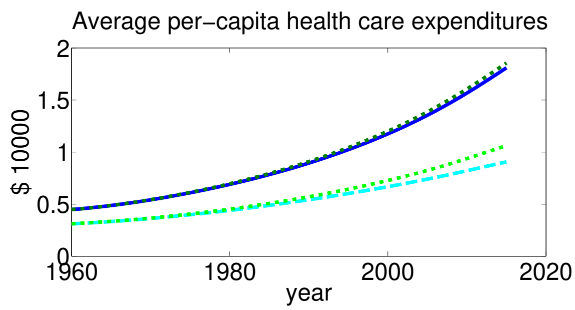

Figure 6: Average health care expenditures for skilled (blue, solid in the benchmark and dark-green, dotted in the counter-factual I) and unskilled (cyan, dashed in the benchmark and light-green, dotted in the counter-factual I)

Overall, the gap in life-expectancy (calculated as the difference in life expectancy at each point in time) between the skill groups grows at a smaller pace in the counter-factual as visualised in Figure 7.

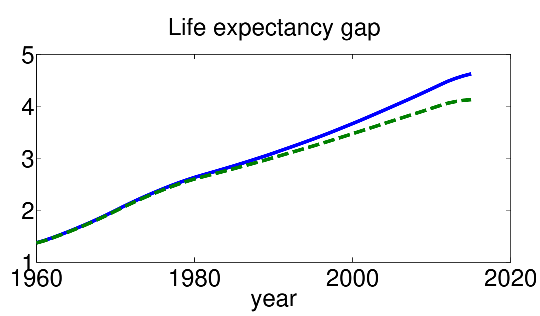

Figure 7: Evolution of life expectancy gap: Benchmark (blue, solid) and counterfactual I where earnings grow at same rate (green, dashed)

3.2.3 Counterfactual II: No medical price inflation

In this counterfactual we explore whether the inflation in the price for health care, as is induced by productivity growth in the final goods sector, exacerbates or mitigates inequality in the access to health care and the resulting gap in life expectancy. Here, one concern may be that the unskilled are doubly punished by not participating in productivity-driven increases in earnings while at the same time being exposed to price inflation in the health care sector. Thus, we consider a counterfactual scenario in which we fix to a constant level the price for health care from 1980 onward, as is depicted in Figure 8. Note that this implies that from 1980 onward the health care market does not actually clear in the counterfactual.

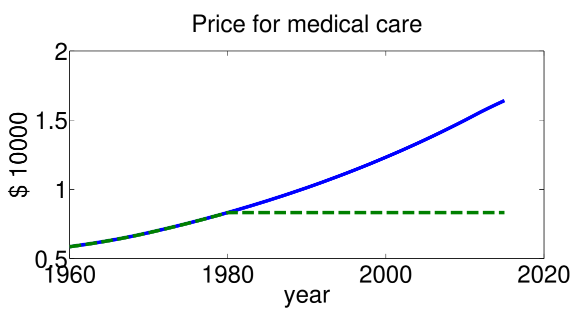

Figure 8: Evolution of the price for medical care $p_H(t)$: Benchmark (blue, solid) and counter-factual II where p_H is constant (green, dashed)

In the absence of medical price inflation, the average demand for health care rises for both groups relative to the benchmark (see right panel in Figure 9) while average health care expenditures fall within both groups (see left panel in Figure 9). Note that this is consistent with a demand elasticity of health care below one (McGuire 2012). As a consequence of the greater demand for health care in the absence of medical price inflation, life-expectancy rises for both groups relative to the benchmark (Figure 10) .

Notably, this has no significant effects on the life-expectancy gap, as seen in Figure 11.

Indeed, in the absence of medical price inflation (from 1980 onward) both groups would

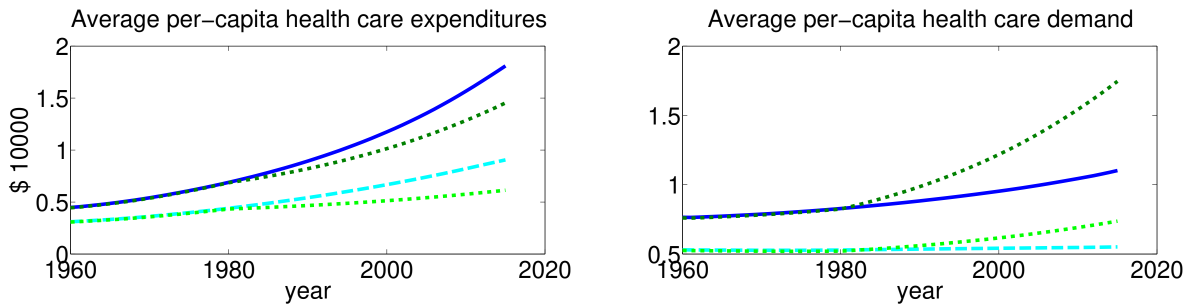

Figure 9: Average health care expenditures $p_H H_j/N_j$ and demand H_j/N_j for the skilled $j = s$ (blue, solid in the benchmark and dark-green, dotted in the counterfactual II) and unskilled $j = u$ (cyan, dashed in the benchmark and light-green, dotted in the counterfactual II).

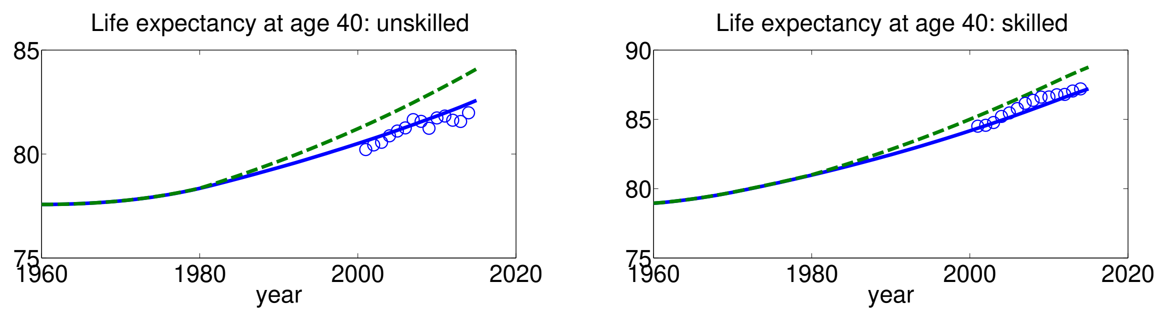

Figure 10: Evolution of life expectancy: Benchmark (blue, solid) and counterfactual II where p_H is constant (green, dashed).

face an increase in life expectancy by about 1.6 years. Thus, while medical price inflation slows down in a substantial way the expansion in life expectancy, it does not increase the gap. As the right panel in Figure (9) shows, medical price inflation curbs the demand for health care for the skilled to a greater extent. In and of itself, this would suggest even a closure in the life expectancy gap, which is (marginally) true. This effect, in turn, however is offset by the fact that due to decreasing returns of health care, the reduction in health care from a lower level leads to a larger increase in mortality for the unskilled.

Despite the absence of a sizeable impact on the longevity gap, medical price inflation is more harmful for the low skilled if measured by the *relative* reduction in the potential increase in life expectancy: Here, medical price inflation reduces by 16% the potential gain of 9.8 life-years in the counterfactual for the skilled, whereas it curbs by 24% the potential

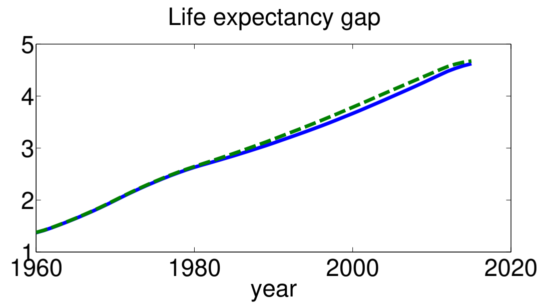

Figure 11: Evolution of life expectancy gap: Benchmark (blue, solid) and counter-factual II where p_H is constant (green, dashed)

gain of 6.6 life-years for the unskilled.

3.2.4 Counterfactual III: No skill-bias in medical technology

This counterfactual explores the role of skill-bias in the access to (or in the use of) state-of-the-art medical technology. Thus, in the following graphs, the green, dashed line refers to a counterfactual scenario in which there is no lag in the evolution of medical technology available to the unskilled, such that $M_u(t) = M_s(t)$. As Figure 12 shows the immediate access to state-of-the-art medical technology boosts the increase in life-expectancy among the unskilled and induces a much smaller gap in life-expectancy.

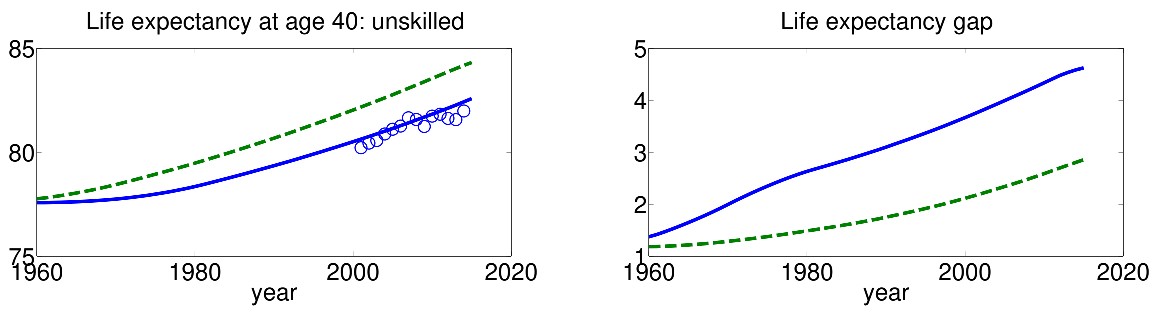

Figure 12: Evolution of life expectancies and life-expectancy gap:Benchmark (blue, solid) and counter-factual with $M_u(t) = M_s(t)$ (green, dashed)

Surprisingly, the immediate access to effective health care does not raise, however, the average health care spending among the unskilled in any substantive way (see Figure 13).[23] Thus, the overall effect is explained by the change in medical effectiveness alone.

[23] At the level of the individual, it can be verified that health care expenditure is deferred to later stages of the life-cycle, but this does not lead to an increase in per capita spending among the unskilled.

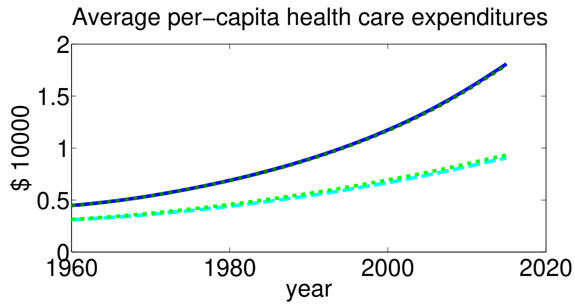

Figure 13: Average health care expenditures for skilled (blue, solid in the benchmark and dark-green, dotted in the counter-factual III) and unskilled (cyan, dashed in the benchmark and light-green, dotted in the counter-factual I)

3.3 Decomposition

We conclude our analysis by considering the isolated contributions of skill-biased earnings growth [counterfactual (i)] and skill-biased access to medical technology [counterfactual (iii)] against a final counterfactual (iv) in which we assume the absence of skill-bias in both directions. We focus here on the gap in life expectancy, as depicted in Figure 14.

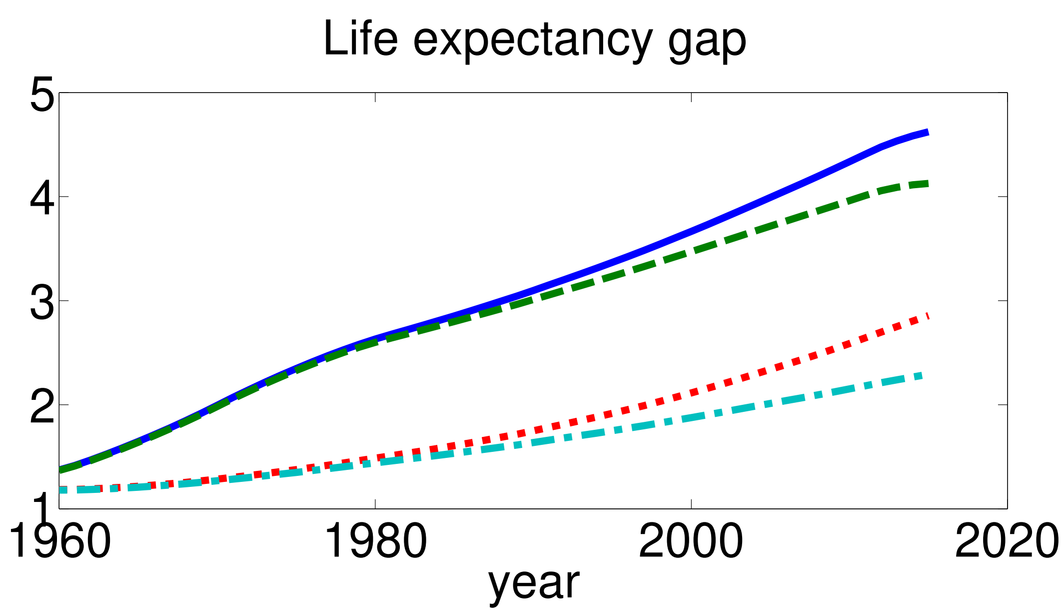

Figure 14: Evolution of life expectancy gap: Benchmark (blue, solid); counterfactual I: no skill-bias in earnings growth (green, dashed); counterfactual III: no skill-bias in access to medical technology (red, dotted); counterfactual IV: no skill-bias in both directions (cyan, dash-dotted).

In the benchmark, the life-expectancy gap rises from 1.3 years in 1960 to 4.4 years in 2015 (blue, solid line) amounting to an increase by 3.1 years. Absent the bias in earnings growth, the gap only grows to 3.9 years (green, dashed), i.e. it increases by 2.6 years. Absent the bias in the access to medical technology the gap grows to 2.8 years (red, dotted), i.e. it increases by 1.5 years. Hence, skill-bias in the access to the most advanced medical technology is able to account for 52% of the increase in the longevity gap, while differential earnings growth explains 16%. In counterfactual (iv) in which we assume the simultaneous absence of skill-bias in both earnings growth and in the access to medical technology, the life expectancy gap increases to only 2.3 years (cyan, dash-dotted). Hence, about 67 % of the overall increase in the life expectancy gap is explained by the combined bias in earnings growth and in the access to medical technology. As this is approximately equal to the sum of each of the biases' individual contributions, this suggests there is no strong complementarity between earnings growth and differential access to the latest medical technology in explaining the emergence of the longevity gap.

Remarkably, however, 33% of the increase [amounting to the 1.0 year increase in the longevity gap in counterfactual (iv)] are explained by income-related differences in the use of medical technology. Although the income gap is assumed not to widen beyond its initial 1960 value, the persistence of a (constant) income gap in itself induces a widening of the longevity gap. This is because medical progress renders the use of a given quantity of health care more and more effective over time. On top, the propensity to expend on increasingly effective health care increases at a higher rate for the top earners due to complementarity between income and medical progress Thus, any given gap in income generates more and more diverse outcomes over time, reflecting the lower capacity of the unskilled to participate in the gains of medical progress.

4 Conclusions

We have studied an overlapping generations model in which representatives of two groups, the skilled and the unskilled, consume and purchase health care toward extending their longevity. The unskilled are subject to three disadvantages: they face lower earnings to begin with, they face lower earnings growth due to skill-biased technological change, and they face a lag in access to the most effective medical technology. Based on a calibration of the model to reflect the US economy and health care system over the time span 1960-2005 we study the extent to which these three disadvantages explain the emerging longevity gap between the recipients of the top 50% (net) income and the recipients of the bottom 50%. We find that while all three channels contribute to the emergence of the longevity gap, differential earnings growth itself explains the least of the increase while skill-bias in the access to advanced medical technology plays a strong part. Notably, however, even in the presence of symmetric access to medical progress, the skilled are increasingly prone to benefit relative to the unskilled due to their higher propensity to spend on health care into which medical progress is "embedded". Our results clearly suggest that a policy-maker concerned about unequal access to health care should not only mitigate a divergent ability of different social groups to spend on health care but enable disadvantaged group to access the most effective forms of health care. Thus, policies based on the provision of information and targeted primary care programmes that facilitate the access to advanced and complex hospital care and/or pharmaceutical therapies may prove to be more effective than a pure redistribution of income. Furthermore, even if the widening of the income gap can be stopped, this would not yet stop the widening of the longevity gap that comes with continued medical progress. To arrive at such an objective, the income gap would effectively have to be closed.

While our model offers a first theory-guided perspective on the channels through which socioeconomic inequality drives inequality in longevity, two open issues merit further attention. First, by considering a fixed population that is split into the 50 percent top earners as opposed to the 50 percent bottom earners our current model abstracts from the way in which the income distribution relates to the distribution of skills or education for that matter. We believe this stylization to be immaterial for our current results as (i) educational choices are not the focus of this analysis; and (ii) the evolution of wages is taken from the data and, as such, reflects the dynamics of the underlying education/skill structure. Our modelling of a population cleanly structured by the 50 % top and bottom earners then has the merit of allowing a clean attribution of effects within and across the two groups. It does rule out, however, the study of societal and/or policy changes that lead to changes in the educational distribution. There is clear merit in gaining an understanding how these changes themselves determine the shape of the income distribution in a richer model in which wages are not just driven by exogenous changes in productivity but also in the size and labour supply of the different skill groups. Second, we currently assume that health only bears on longevity, whereas in reality the feedback channel of health on labour supply and, thus, on income is prone to play an important role. This is particularly true for the unskilled who typically face health-related restrictions in their labour supply fairly early on in life. We relegate these extensions to further study.

5 Appendix

5.1 Optimal Solution to the Individual Life-cycle Problem

For notational convenience, we drop here the group index i. The individual's life-cycle problem, i.e. the maximisation of (1) subject to (2) and (3) can be expressed by the Hamiltonian

$$\mathcal{H} = uS - \lambda_S \mu S + \lambda_k \left(rk + lw - c - \phi p_H (h + e) - \tau + \pi + s \right),$$

leading to the first-order conditions

$$\begin{aligned}\mathcal{H}_c &= u_c S - \lambda_k = 0, &(28)\\ \mathcal{H}_h &= -\lambda_S \mu_h S - \lambda_k \phi p_H = 0, &(29)\end{aligned}$$

and the adjoint equations

$$\begin{aligned}\dot{\lambda}_S &= (\rho + \mu)\lambda_S - u + \lambda_k \phi p_H e_S, &(30)\\ \dot{\lambda}_k &= (\rho - r)\lambda_k. &(31)\end{aligned}$$

Evaluating (28) at two different ages/years (a,t) and $(\widehat{a}, t+\widehat{a}-a)$, equating the terms and rearranging gives us

$$\begin{aligned}\frac{u_c(\widehat{a}, t+\widehat{a}-a)}{u_c(a,t)} &= \frac{\lambda_k(\widehat{a}, t+\widehat{a}-a)}{\lambda_k(a,t)} \frac{S(a,t)}{S(\widehat{a}, t+\widehat{a}-a)}\\ &= \exp\left\{\int_a^{\widehat{a}} \left[\rho + \mu\left(\widehat{\widehat{a}}, t+\widehat{\widehat{a}}-a\right) - r\left(t+\widehat{\widehat{a}}-a\right)\right] d\widehat{\widehat{a}}\right\}, &(32)\end{aligned}$$

which is readily transformed into the Euler equation (18) as given in the main body of the paper.

Inserting (28) into (29) allows to rewrite the first-order condition for health care as

$$-\mu_h(a,t)\frac{\lambda_S(a,t)}{u_c(\cdot)} = \phi(a,t)\, p_H(t). \quad (33)$$

Integrating (30) we obtain

$$\lambda_S(a,t) = \int_a^{\omega} \left[u(\widehat{a}, t+\widehat{a}-a) - u_c \phi p_H e_S S(\widehat{a}, t+\widehat{a}-a)\right] \exp\left[-\int_a^{\widehat{a}} (\rho+\mu)\, d\widehat{\widehat{a}}\right] d\widehat{a},$$

Using this, we can express the value of survival as

$$\begin{aligned}\psi(a,t) &:= \frac{\lambda_S(a,t)}{u_c(a,t)}\\ &= \int_a^{\omega} \frac{u_c(\widehat{a}, t+\widehat{a}-a)}{u_c(a,t)} \left(\frac{u(\widehat{a}, t+\widehat{a}-a)}{u_c(\widehat{a}, t+\widehat{a}-a)} - \phi p_H e_S S(\widehat{a}, t+\widehat{a}-a)\right) \exp\left[-\int_a^{\widehat{a}} (\rho+\mu)\, d\widehat{\widehat{a}}\right] d\widehat{a}.\end{aligned}$$

Inserting from (32) and rearranging appropriately gives (20) in the main body of the paper. Inserting this in turn into (33) then gives (19) in the main body of the paper.

5.2 Equilibrium Relationships with Cobb-Douglas Technologies

Perfectly competitive firms in the production sector choose labour $L_s^Y(t), L_u^Y(t)$ and capital $K_Y(t)$ so as to maximise period profit (12) subject to the production technology in (13). Likewise, providers of health care choose labour $L_s^H(t), L_u^H(t)$ and capital $K_H(t)$ so as to maximise period profit (14) subject to (15). The first-order conditions imply

$$\begin{aligned} r(t) &= Y_K(t) - \delta = p_H(t) F_K(t) - \delta, && (34)\\ w_s(t) &= A_s^Y(t) Y_L(t) = p_H(t) A_s^H(t) F_L(t), && (35)\\ w_u(t) &= A_u^Y(t) Y_L(t) = p_H(t) A_u^H(t) F_L(t), && (36) \end{aligned}$$

i.e. the factor prices are equalised with their respective marginal products. From (35) and (36) it follows, immediately that the ratio of skilled vs. unskilled labour productivity must satisfy

$$\frac{w_s(t)}{w_u(t)} = \frac{A_s^H(t)}{A_u^H(t)} \equiv \frac{A_s^Y(t)}{A_u^Y(t)}$$

across both sectors at all times. Inserting the appropriate derivatives from (13) and (15) into the first-order conditions (34)-(36) we obtain

$$\begin{aligned} K_Y(t) &= \frac{\alpha Y(t)}{r(t)+\delta}, && (37)\\ K_H(t) &= \frac{\beta p_H(t) F(t)}{r(t)+\delta}, && (38)\\ A_s^Y(t) L_s^Y(t) + A_u^Y(t) L_u^Y(t) &= A_s^Y(t) \frac{(1-\alpha)Y(t)}{w_s(t)} = A_u^Y(t) \frac{(1-\alpha)Y(t)}{w_u(t)}, && (39)\\ A_s^H(t) L_s^H(t) + A_u^H(t) L_u^H(t) &= A_s^H(t) \frac{(1-\beta)p_H(t)F(t)}{w_s(t)} = A_u^H(t) \frac{(1-\beta)p_H(t)F(t)}{w_u(t)} && (40) \end{aligned}$$

Inserting (13) and (37) into the LHS part of (39) and rearranging yields the following expression:

$$w_s(t) = A_s^Y(t)(1-\alpha)\left(\frac{\alpha}{r(t)+\delta}\right)^{\alpha/(1-\alpha)}. \qquad (41)$$

Analogously, we can derive

$$\begin{aligned} w_u(t) &= A_u^Y(t)(1-\alpha)\left(\frac{\alpha}{r(t)+\delta}\right)^{\alpha/(1-\alpha)} && (42)\\ w_i(t) &= (p_H(t))^{1/(1-\beta)} A_i^H(t)(1-\beta)\left(\frac{\beta}{r(t)+\delta}\right)^{\beta/(1-\beta)}, \quad i = s,u && (43) \end{aligned}$$

From this we obtain

$$p_H(t) = \left(\frac{w_s(t)}{A_s^H(t)}\right)^{1-\beta} \frac{(r(t)+\delta)^\beta}{\beta^\beta(1-\beta)^{1-\beta}} = \left(\frac{w_u(t)}{A_u^H(t)}\right)^{1-\beta} \frac{(r(t)+\delta)^\beta}{\beta^\beta(1-\beta)^{1-\beta}}. \tag{44}$$

We now determine the labor shares across sectors and skill groups. To do so we first observe that the labor supply in the population is given by

$$L(t) = \int_a^w l_s(a) N_s^c(a,t)da + \int_a^w l_u(a) N_s^c(a,t)da = L_s(t) + L_u(t). \tag{45}$$

We now define $z_s(t) := L_s(t)/L(t)$ as the share of effective labor supply by the skilled in total labor supply. As the relative productivity of the skilled to the unskilled is identical across both sectors and given by $w_s(t)/w_u(t)$, the share of skilled labour in each sector is identical and also given by λ_s. From (40) it then follows that

$$A_s^H(t)L_s^H(t) + A_u^H(t)\frac{1-z_s(t)}{z_s(t)}L_s^H(t) = A_s^H(t)\frac{(1-\beta)p_H(t)H(t)}{w_s(t)},$$

where we used the market clearing condition $H(t) = F(t)$. It is then straightforward to derive

$$L_s^H(t) = \frac{A_s^H(t)(1-\beta)p_H(t)H(t)}{w_s(t)\left(A_s^H(t) + A_u^H(t)\frac{1-z_s(t)}{z_s(t)}\right)}.$$

Using the labor market clearing conditions, it is then trivial to arrive at $L_u^H(t), L_s^Y(t)$ and $L_u^Y(t)$. Finally K_H can be deduced from (38) and K_Y from the capital market clearing condition.

5.3 Solving the Numerical Problem

We pursue the following steps towards tracing out the numerical solution, sketched here for the benchmark scenario, while using the specific functional forms presented in section 3:

1. We derive from the first-order condition for consumption (18) the relationship

$$c_i\,(a, t_0 + a)^{-\sigma} = c_i\,(0, t_0)^{-\sigma} \exp\left\{\int_0^a \left[\rho - r(t_0 + \hat{a}) + \mu_i(\hat{a})\right] d\hat{a}\right\}. \tag{46}$$

   for $i = s, u$.

2. We derive the life-cycle budget constraint

$$\int_0^\omega \left[\begin{array}{c} w_i\,(t_0+a)\,l_i\,(a) - c_i\,(a, t_0+a) + \pi_i(a,t) \\ -\phi_i(a,t)p_H\,(t_0+a)\,(h_i\,(a,t_0+a) + e_i\,(a,t_0+a)) - \tau_i(a,t) + s_i(t_0+a) \end{array}\right] R\,(a,0)\,da = 0,$$

   with $R\,(a,0)$ as given by

$$R(\widehat{a},a) := \exp\left[-\int_a^{\widehat{a}} r\left(t+\widehat{\widehat{a}}-a\right) d\widehat{\widehat{a}}\right]. \tag{47}$$

We then insert (46) and obtain the consumption level

$$c_i(0,t_0) = \frac{\int_0^\omega \left[\begin{array}{c} w_i(t_0+a)\,l_i(a)+\pi_i(a,t)-\tau_i(a,t)+s_i(t_0+a) \\ -\phi_i(a,t)p_H(t_0+a)\left(h_i(a,t_0+a)+e_i(a,t_0+a)\right)\end{array}\right] R(a,0)\,da}{\int_0^\omega \exp\left\{\int_0^a\left[\frac{1-\sigma}{\sigma}r(t_0+\hat{a})-\frac{\rho+\mu_i(\hat{a})}{\sigma}\right]d\hat{a}\right\}da} \tag{48}$$

for an individual born at t_0, contingent on the stream of health care, $h_i(a,t_0+a)$, and the set of prices $\{w_i(t_0+a), r(t_0+a), p_H(t_0+a)\}$ over the interval $[t_0,t_0+\omega]$. Finally, we need to keep track of the constraint on minimum consumption at the level of social security benefits. As is readily checked from the numerical analysis, this constraint is binding only at the highest ages.

3. We derive from the first-order condition for health care (19) a vector of age-specific demand levels

$$h_i(a,t_0+a) = \left(\frac{\psi_i(a,t_0+a)\eta(a)(-\kappa)M_i(t_0+a)}{\phi_i(a,t_o+a)p_H(t_0+a)}\right)^{\frac{1}{1-M(t_0+a)\kappa}} \tag{49}$$

for all $a\in[0,\omega]$.

4. We show in section 5.2 that the set of prices $\{w_i(t_0+a), p_H(t_0+a)\}$ as well as all input and output quantities can be expressed in terms of the interest rate $r(t_0+a)$ alone.

5. Using (46) together with (49) we can calculate the life-cycle allocation for consumption, $c_i(a,t_0+a)$, depending on the allocation for health expenditures, $h_i(a,t_0+a)$, $\forall a\in[0,\omega]$ and on the set of prices $\{w_i(t_0+a), r(t_0+a), p_H(t_0+a)\}$ over the interval $[t_0,t_0+\omega]$. Vice versa, the allocation of health expenditures can be calculated from the allocation of consumption and the macroeconomic prices.

6. We apply these calculations iteratively on initial guesses of c and h. We then use the results as an initial guess to the age-structured optimal control algorithm, as presented in Veliov (2003). This yields an optimal allocation of individual consumption and health expenditures contingent on an initially assumed $r(t_0+a)$.

7. Drawing on this, we apply the following recursive approximation algorithm: (i) Guess an initial interest rate $r(t_0+a)$ and derive the optimal life-cycle allocation. (ii) Based on this, calculate the market interest rate $r^*(t_0+a)$ from the capital market equilibrium $K^d(r(t_0+a),\widehat{w}(r(t_0+a))) = K^s(r(t_0+a))$. (iii) Adjust the initial interest rate, so that it approaches $r^*(t_0+a)$, e.g. by setting $r_1(t_0+a) := r_0(t_0+a)+\epsilon(r^*(t_0+a)-r_0(t_0+a)),\quad \epsilon\in(0,1]$. The process converges to an interest

rate for which households optimize and capital demand equals capital supply. The output market clearing condition, $Y(t_0+a) = C(t_0+a)+\dot{K}(t_0+a)+\delta K(t_0+a)$ then determines the dynamics of the capital stock to the next period. (iv) This process is reiterated in a recursive way, employing a solution algorithm based on Newton's method. Equations (46)-(49) allow us to verify ex-post an optimum life-cycle allocation for the focal cohort born at t_0. While the numerical algorithm cannot determine in a precise way the optimal allocation for other cohorts, it nevertheless structures the allocation in a way that approximates the optimum for all cohorts.

References

[1] Acemoglu D and D Autor (2011), Skills, tasks and technologies: implications for employment and earnings, chapter 12, in: Card D and O Ashenfelter (eds.), Handbook of Labor Economics, Vol. 4B, Elsevier: North-Holland.

[2] Acemoglu D and V Guerrieri (2008), Capital Deepening and Nonbalanced Economic Growth, Journal of Political Economy 116, 467-498.

[3] Ales L, R Hosseini and LE Jones (2014), Is there "too much" inequality in health spending across income groups? Mimeo.

[4] Avitabile C, T Jappelli and M Padula (2011), Cognitive abilities, health care and screening tests, Journal of Population Ageing 4, 251-269.

[5] Bago d'Uva T and AM Jones (2009), Health care utilitzation in Europe: new evidence from the ECHP, Journal of Health Economics 28, 265-279.

[6] Baumol WJ (1967), Macroeconomics of unbalanced growth: the anatomy of urban crisis, American Economic Review 57, 415-426.

[7] Böhm S, V Grossmann and H Strulik (2017), R&D-driven medical progress, health care costs, and the future of human longevity, mimeo.

[8] Capatina E (2015), Life-cycle effects of health risk, Journal of Monetary Economics 74, 67-88.

[9] Case A and A Deaton (2017), Mortality and morbidity in the 21st century. Brookings Papers on Economic Activity, Conference Draft.

[10] Chandra A and J Skinner (2012), Technology growth and expenditure growth in health care, Journal of Economic Literature 50, 645-680.

[11] Chetty R, M Stepner, S Abraham, S Lin, B Scuderi, N Turner, A Bergeron and D Cutler (2016), The association between income and life expectancy in the United States, 2001-2014, Journal of the American Medical Association 315, 1750-66.

[12] Clouston SAP, MS Rubin, DH Chae, J Freese, B Nemesure, BG Link (2017), Fundamental causes of accelerated declines in colorectal cancer mortality: modeling multiple ways that disadvantage influences mortality risk, Social Science & Medicine 187, 1-10.

[13] Cole HL, S Kim and D Krueger (2018), Analyzing the effects of insuring health risks. Review of Economic Studies, forthcoming.

[14] Congressional Budget Office (2016), The Distribution of Household Income and Federal Taxes, 2013, (Online). Available: https://www.cbo.gov/publication/51361, Referenced: Feb 2, 2018.

[15] Congressional Research Office (2017), The Growing Gap in Life Expectancy by Income: Recent Evidence and Implications for the Social Security Retirement Age, (Online), available: https://fas.org/sgp/crs/misc/R44846.pdf. Referenced: Feb 2, 2018.

[16] Dalgaard C-J and H Strulik (2014), Optimal Aging and Death: Understanding the Preston Curve, Journal of the European Economic Association 12, 672-701.

[17] Fiva JH, T Haegeland, M Roenning and A Syse (2014), Access to treatment and educational inequalities in cancer survival, Journal of Health Economics 36, 98-111.

[18] Fonseca R, P-C Michaud, A Kapteyn and T Galama (2013), Accounting for the rise of health spending and longevity, IZA Discussion Paper No. 7622.

[19] Frankovic I and M Kuhn (2018), Health insurance, endogenous medical progress, and health expenditure growth, TU Vienna Econ Working Paper 01/2018.

[20] Frankovic I, M Kuhn and S Wrzaczek (2017), Medical progress, demand for health care, and economic performance, TU Vienna Econ Working Paper 08/2017.

[21] Getzen TE (2000), Health care ia an individual necessity and a national luxury: applying multilevel decision models to the analysis of health care expenditures, Journal of Health Economics 19, 259-270.

[22] Glied S and A Lleras-Muney (2008), Technological innovation and inequality in health, Demography 45, 741-761.

[23] Goldman DP and DN Lakdawalla (2005), A theory of health disparities and medical technology, BE Contributions to Economic Analysis & Policy 4(1), Article 8.

[24] Goldman D and JP Smith (2005), Socioeconomic differences in the adoption of new medical technologies, American Economic Review (Papers & Proceedings) 95, 234-237.

[25] Hagen TP, H Häkkinen, T Iversen, ST Klitkou, and TA Moger (2015), Socio-economic inequality in the use of proucedures and mortality among AMI patients: quantifying the effects along different paths, Health Economics 24, 102-115.

[26] Hall RE and CI Jones (2007), The Value of Life and the Rise in Health Spending, Quarterly Journal of Economics 122, 39-72.

[27] Hernandez EM, R Margolis and RA Hummer (2018), Educational and gender differences in health behavior changes after a gateway diagnosis, Journal of Aging and Health 30, 342-364.

[28] Hummer RA and EM Hernandez (2013), The effect of educational attainment on adult mortality in the United States, Population Bulletin 68, 1-16.

[29] Jones CI (2016), Life and growth, Journal of Political Economy 124, 539-578.

[30] Koijen RSJ, TJ Philipson and H Uhlig (2016), Financial health economics, Econometrica 84, 195-242.

[31] Korda RJ, MS Clments and J Dixon (2011), Socioeconomic inequalities in the diffusion of health technology: uptake of coronary procedures as an example, Social Science & Medicine 72, 224-229.

[32] Kuhn M, S Wrzaczek, A Prskawetz and G Feichtinger (2015), Optimal choice of health and retirement in a life-cycle model, Journal of Economic Theory 158A, .186-212.

[33] Lange F (2011), The role of education in complex health decisions: evidence from cancer screening, Journal of Health Economics 30,.43-54.

[34] McGuire TG (2012), Demand for health insurance, chapter 5 in: Pauly MV and PG Barros (eds.), Handbook of Health Economics Vol. 2, Elsevier: North-Holland.

[35] OECD (2017), Preventing ageing unequally, OECD Publishing: Paris.

[36] Ozkan S (2014), Preventive vs. curative medicine: a macroeconomic analysis of health care over the life cycle. Mimeo.

[37] Phelan JC and BG Link (2005), Controlling disease and creating disparities: a fundamental cause perspective, Journal of Gerontology, Series B 60, Speical Issue 2, S27-S33.

[38] Prados MJ (2013), Health and earnings inequality over the life cycle: the redistributive potential of health policies. Mimeo.

[39] Rockwood K and A Mitnitski (2007), Frailty in Relation to the Accumulation of Deficits, Journal of Gerontology: Medical Sciences 62A, 722-727.

[40] Schneider MT and R Winkler (2016), Growth and welfare under endogenous life-time, University of Bath: Bath Economics Research Papers No. 47/16.

[41] Schröder SL, M Richter, J Schröder, S Frantz and A Fink (2016), Socioeconomic inequalities in access to treatment for coronary heart disease: a systematic review, International Journal of Cardiology 219, 70-78.

[42] Sheiner L and A Malinovskaya (2016), Measuring of productivity in health care: an analysis of the literature, Hutchins Center on Fiscal and Monetary Policy at Brookings.

[43] Skinner J and W Zhou (2004), The measurement and evolution of health inequality: evidence from the US Medicare population, NBER Working Paper 10842.

[44] Suen, RMH (2009), Technological advance and the growth in health care spending. Mimeo.

[45] Truesdale BC and C Jencks (2016), The health effects of income inequality: averages and disparities, Annual Review of Public Health 37, 413-430.

[46] Vallejo-Torres L and S Morris (2013), Income-related inequality in health care utilisation amon individuals with cardiovascular disease in England - accounting for vertical inequity, Health Economics 22, 533-553.

[47] Veliov VM (2003), Newton's method for problems of optimal control of heterogeneous systems, Optimization Methods and Software 18(6), 689-703.

[48] Viscusi WK and Aldy JE (2003), The Value of a Statistical Life: A critical Review of Market Estimates Throughout the World, The Journal of Risk and Uncertainty 27(1), 5-76.

[49] Wang A, SAP Clouston, MS Rubin, CG Colen and BG Link (2012), Fundamental causes of colorectal cancer mortality: the implications of informational diffusion, Milbank Quarterly 90, 592-618.

[50] Woolf SH and P Braveman (2011), Where health disparities begin: the role of social and economic determinants - and why current policies may make matters worse, Health Affairs 30, 1852-1859.

[51] Zweifel P, S Felder and M Meier (1999), Ageing of population and health care expenditure: a red herring? Health Economics 8, 485-496.