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Medical innovation and its diffusion: Implications for economic performance and welfare☆

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ABSTRACT

We study the impact on economic performance and welfare of medical innovations and their endogenous diffusion. We construct a general equilibrium model with a medical sector and overlapping generations subject to endogenous mortality and calibrate it to reflect the development of the US economy and health care over the cardiac revolution during the 1980s and 1990s. By counterfactual analysis we find that (i) medical innovations have increased welfare without compromising GDP growth; (ii) there is a sizeable welfare loss due to the adoption lag involved with imperfect diffusion; and (iii) there is scope for Pareto improvement by way of subsidization of innovative health care.

1. Introduction

A consensus has emerged that medical progress is driving both the increase in health care spending and the increase in longevity (e.g. Cutler, 2004; Suen, 2009; Chandra and Skinner, 2012; Chernew and Newhouse, 2012; Fonseca et al., 2020) that is observed in the US and many other developed countries.[1] In the US, the intensity at which medical innovations were transforming the provision of health care was unprecedented during the 1980s and 1990s, a period sometimes referred to as the "cardiac revolution". OECD (2018) data on the causes of death in the US shows that most of the decline in aggregate mortality during the 1980s and 1990s could be attributed to a decline in mortality from coronary (or ischemic) heart disease. Ford et al. (2006) attribute about 50 percent of this decline to the use of innovative medical treatments, the remainder being explained by behavioral changes. Given that competing medical innovations, e.g. against cancer, did not play a significant role in curbing mortality during the 1980s and 1990s, this makes the cardiac revolution a good testbed for studying the implications of medical progress.

Two issues in the context of medical innovations seem to warrant particular concern. First, there is strong evidence that medical innovations tend to boost the utilization of health care (e.g. Baker et al., 2003; Wong et al., 2012; Roham et al., 2014) and this was

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[1] Other important drivers include income (Hall and Jones, 2007) and the presence of social security (Zhao, 2014).

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certainly the case during the cardiac revolution (Cutler and Huckman, 2003). This does not only imply an increase in health care expenditure but it reflects a significant absorption of production factors that may be employed more productively in other sectors of the economy (Pauly and Saxena, 2012; Kuhn and Prettner, 2016). An examination of this concern warrants a general equilibrium analysis to keep track of the way in which the increase in the demand for health care that is induced by medical progress leads to changes in the sectoral structure of the economy and of how this affects economic performance.

A second issue that has attracted recent interest, not the least in the context of the cardiac revolution, relates to the diffusion of new medical technologies (Cutler and Huckman, 2003; Skinner and Staiger, 2015). The adoption of medical technologies and their effective use by medical doctors, hospitals and other providers of health care follows a process of diffusion which shapes the time lag at which innovative medicine becomes available to a large number of patients. According to evidence by Skinner and Staiger (2015) the diffusion of medical technologies is remarkably slow; it is also subject to economic incentives and the interaction of economic agents in the form of spillovers and competition (Chandra and Staiger, 2007; Baicker and Chandra, 2010; Gravelle et al., 2014; Agha and Molitor, 2018; Molitor, 2018). This raises issues about how the diffusion process itself is shaped by the development of the market over time, about the potential welfare loss arising from slow diffusion, as well as about the scope for policy making towards improving it. While Skinner and Staiger (2015) provide a model of diffusion at the provider level, the macroeconomic ramifications of the diffusion process have not yet been studied in a rigorous way.

In this paper, we examine the impact of medical innovations on economic performance and welfare when these innovations are subject to a process of endogenous diffusion. Specifically, we seek to provide answers to the following set of questions: (i) Given we are observing a strong expansion of the health share in response to medical progress, is this harmful to macroeconomic performance and welfare? (ii) What welfare loss arises from the imperfect diffusion of medical innovation over time, and could it possibly be mitigated by way of subsidization of innovative health care?

We study these issues by analyzing an overlapping generations (OLG) model with realistic demography in which individuals demand health care to reduce mortality.[2] Health care is provided within a medical sector that employs capital and labor and, thereby, competes for these production factors with a final goods sector. We assume that at each point in time an exogenous flow of medical innovations is adopted by a limited share of providers. The commonly available medical technology then follows the medical frontier only with a time lag. We derive the optimal life-cycle allocation in terms of consumption and health care as well as the general equilibrium. Based on this, we characterize the structure of supply and demand on the input and output markets as well as the aggregate dynamics.

We employ our model to analyze numerically the impact of medical progress against coronary heart disease in the US during the cardiac revolution. We calibrate our model to capture the impact of medical innovations in the treatment of heart disease on mortality as well as the development of the US economy and its health care sector over the time span 1970–2005. This includes the cardiac revolution, which we assume to take place from 1980 up until 2005, and which is the time frame we study in counterfactual analysis. In modeling the diffusion of medical innovations we take into account recent evidence and insights on diffusion processes within the health care sector and more generally. We provide a more detailed description of some features of diffusion in the following section.

Our analysis proceeds in two steps. We first establish a benchmark scenario in which we capture key aspects of the development of the US economy, demography and health care sector over the time span 1970–2005, as well as key features of the diffusion process. Against this benchmark, we then study three counterfactual scenarios: (i) a counterfactual in which we assume the absence of medical innovation beyond 1980; (ii) a counterfactual in which we assume that medical innovations are instantaneously available from 1980 onwards; and (iii) a counterfactual in which we study how the subsidization of innovative health care can speed up the diffusion of state-of-the-art medicine. Our key findings are as follows. According to our analysis, medical innovation in coronary heart treatments from 1980 onwards have contributed to an increase in life expectancy in 2005 by about 0.8 years. The perfect diffusion of these innovations would have added another 0.6 years by 2005. At the same time, medical progress against heart disease has boosted the annual growth rate of per capita spending on health care by 1.2 percentage points, thus explaining 35% of the spending increase over the time span 1980–2005. Although this leads to an additional boost in the health expenditure share by some 3.5 percentage points in 2005, the strong expansion of the health care sector does not impose a drag on GDP per capita. This is because the drop in the employment rate that comes with a disproportionate increase in survival amongst the retired population is overcompensated by the accumulation of additional wealth for the purpose of financing consumption and (more effective) health care over an extended life span.

While medical progress is associated with a significant increase in the Medicare tax rate and a reduction in the growth of per capita consumption, we show that all birth cohorts 1910–1980 have benefited from medical innovation over the course of the cardiac revolution from 1980 onwards. The share of consumption individuals would be willing to give up to live in an economy with medical progress as opposed to one without, increases to 50% for the latest-born cohorts who are the beneficiaries of accumulated improvements in medicine. At the same time, we find that the delay in the arrival of state-of-the-art medicine due to imperfections in diffusion causes a welfare loss for all cohorts, this loss again being greatest for the latest-born cohorts amounting to a compensating variation in consumption of around 13%. Finally, we find that the introduction of tax-financed subsidies for the provision of innovative health care, as implied e.g. by the projected Medicare/Medicaid Hospital Inpatient Value-Based Purchasing Program (Blumenthal and Jena, 2013) would lead to sizeable improvements in the diffusion of medical technology. The subsidization of innovative treatments from 1980 onwards at rates around 10% would have yielded sizeable welfare gains across all cohorts.

[2] Recent models that study the economic impact of exogenous changes to mortality include e.g. Prettner (2013) and Mierau and Turnovsky (2014).

While higher subsidy rates would add considerably to the welfare of late-born cohorts, middle-born cohorts tend to prefer more limited subsidization as they are exposed to high levels of taxation for most of their working lives but do not benefit from the full accumulated benefits. The presence of disagreement across cohorts about their preferred rate of subsidization suggests some scope for intergenerational conflict about the financing of a quicker diffusion of innovative medicine.

Our work contributes to an emerging literature on the role of medical progress as a driver of health care spending and longevity. Suen (2009), Kelly (2017) and Fonseca et al. (2020) study the impact of exogenous medical progress on health expenditure growth, life expectancy and, in case of Fonseca et al. (2020), on welfare. These paper differ in focus in as far (a) as they do not account for the sectoral reallocation that governs the impact of medical progress on economic performance and consequently remain silent about this;[3] and (b) as they examine the impact of medical progress across different steady states, whereas we present a fully dynamic analysis of the transmission of medical innovations.[4] The latter is of importance when it comes to the comparison of welfare across different birth cohorts with different propensities to benefit from medical care at different points in time and when it comes to analyzing the role of the diffusion process. Schneider and Winkler (2016) study an endogenous growth economy in which overlapping cohorts of individuals invest in health care in order to lower mortality. Comparing the balanced growth paths associated with different states of medical technology, they find that a technology leading to a higher life expectancy imposes a drag on economic growth but leads to a welfare gain. Schneider and Winkler's (2016) assumption of a uniform mortality rate across all age groups does not allow them to capture properly the age distribution of important variables such as the population or health care expenditure, which in their model is assumed to be chosen once and for all at the beginning of the life-cycle. Schneider and Winkler (2016) study the impact of medical progress by way of comparing balanced growth paths, thus again missing out on the dynamics involved with the diffusion of medical innovations.[5]

While to our knowledge this is the first paper to study within a macroeconomic framework the endogenous diffusion of medical innovations, there are only few works dealing with endogenous medical progress to begin with. Jones (2016) analyzes the interaction of conventional and life-saving R&D but does so within a social planner context. Koijen et al. (2016) study the interaction between financial and real health care markets and find that by lowering R&D investments the premium associated with regulatory risk for e.g. pharmaceutical companies curbs the growth of health care expenditure by more than 3 percent. They do not consider, however, medical innovations towards lowering longevity, which we deem to be the more relevant ones in the context of population aging. Closer in spirit are Böhm et al. (2017) and Frankovic and Kuhn (2018) who consider R&D-driven medical innovations. In Böhm et al. (2017) the demand for medical innovations is determined by a social planner. In Frankovic and Kuhn (2018) the demand for medical innovations is boosted through the expansion of health insurance. In this paper, our focus differs in that we endogenize the diffusion process rather than the innovation process. This implies a different, if complementary, policy context.

The remainder of the paper is structured as follows: The following section presents some background on diffusion processes in health care; Section 3 is devoted to a presentation of the model; Sections 4 and 5 characterize the individual life-cycle allocation and the general equilibrium, respectively; Section 6 introduces the numerical calibration and benchmark scenario; Section 7 studies by way of counterfactual analysis the role of medical progress and imperfect diffusion; and Section 8 wraps up. Some of the proofs as well as a short representation of individual life-cycle outcomes and a version of the model in which providers take deliberate adoption decisions have been relegated to an Online Appendix.

2. Diffusion of medical innovations

Skinner and Staiger (2015) study the diffusion process of three innovative methods in the treatment of heart attacks (administration of aspirin, of beta blockers, and reperfusion within 12 h of an acute myocardial infarction) and how it bears on the survival of patients. Using US Medicare data for the time frame 1986–2004, they estimate diffusion rates for these treatments and find an average diffusion rate of around 7.5 percent in US hospitals in 1995. In line with this, they estimate a time lag between early and late adoption of 5–10 years. All of this suggests a remarkably slow process of diffusion, a fact that applies for the diffusion of innovations more generally (Comin, 2009; Comin and Mestieri, 2010, 2014). Focusing on the treatment of heart disease during roughly the same period of observation, we calibrate our macroeconomic model according to the microeconomic findings by Skinner and Staiger (2015). We should stress that in so doing we adopt a similar interpretation of "innovation": Namely we do not only have in mind "large" isolated technical innovations in the treatment of heart disease, such as percutaneous angioplasty (or stents), but also the more gradual flow of innovations in the administration of these treatments. What we will label "state-of-the-art medicine" or the "medical frontier" will, thus, not only involve technical and pharmaceutical innovations per se but rather the gradual build-up of the know-how for using and combining new treatment methods in an effective way.

One important aspect of the diffusion of medical innovations is the spillover of (often non-codable) knowledge about new treatments and their effective administration. A considerable literature has emerged that documents the relevance of such spillovers

[3] Suen (2009) assumes a single sector economy where final goods are transformed into health care at an exogenous rate that is the inverse of the price of health care. Medical progress is captured by an increase in the transformation rate, which would imply a declining price of health care. Fonseca et al. (2020) consider a partial equilibrium setting, implying there is no scope for price adjustments. In consequence both papers remain focused on explaining the change in longevity and life expectancy but do not allow a proper assessment of the underlying macroeconomic adjustment.

[4] Frankovic et al. (2020) consider a theoretical model similar to the one presented here. They focus on a detailed analysis of the general pathways through which medical progress bears on the economy but do not present a carefully calibrated numerical analysis. Furthermore, their analysis does not consider the diffusion process nor welfare issues.

[5] Other related studies which do not consider medical progress include Zhao (2014) who analyzes the impact of social security on health care spending and survival and finds a substantial positive impact on both; as well as Kelly (2020) who studies the impact of health care reform in the US.

and their dependence on local market conditions. Chandra and Staiger (2007) show that regional variation in treatment patterns of heart disease arise from productivity spillovers, where regional specialization in certain treatment forms improves the outcomes for patients who are especially susceptible to these treatments. Molitor (2018) shows a significant effect of the local environment on the practice style of physicians, where migrating physicians are adjusting their behavior by 0.6–0.8 percentage points for each percentage point change in practice environment. Agha and Molitor (2018) show that new cancer drugs are prescribed at higher rates in regions where the authors of the underlying clinical trials or otherwise highly-cited physicians hold residence. Importantly, they argue that authors of clinical trials tend to be located in regions that exhibit greater activity in general, as measured, for instance, by patient demand.

This last result hints at the relevance of agglomeration effects. Carlino et al. (2007) show that generally it is market density rather than market size that is conducive to knowledge spillovers. The evidence on knowledge spillovers is complemented by evidence on quality spillovers by Baicker and Chandra (2010) and Gravelle et al. (2014) who show for the US and England, respectively, that a hospital's quality, as measured by various indicators, is correlated with its neighbors' qualities at elasticities ranging between 0.16–0.29. Li (2014) shows that while proximity to a doctor improves treatment outcomes, this effect is stronger within urbanized areas, a finding that is consistent with the impact of agglomeration effects on the provision of quality.

Various channels may lie behind spillovers in the adoption of innovative or high quality treatments. Besides direct knowledge spillovers, these may involve the intensity of provider competition (Bokhari, 2009) or the scope for outsourcing (Li, 2013), with both phenomena tending to increase with the density of the market. The idea that the division of labor within denser markets tends to enhance quality is further confirmed by evidence in Clark and Huckman (2012) and Lee et al. (2015) who show that specialization leads to better outcomes in the treatment of cardiovascular and heart disease. Finally, Huesch (2011) shows that the matching between physicians and hospitals matters for the quality of heart treatments. One would conjecture that good matching is facilitated within agglomerated areas with a high density of service provision.

3. The model

3.1. Individual life cycle

We consider an OLG model in which individuals choose consumption and health care over their life-course. Individuals are assumed to be representative within each cohort and are indexed by their age a at time t, with $t_0 = t - a$ denoting the birth year of an individual aged a at time t. At each age, the representative individual is subject to a mortality risk, where $S(a,t) = \exp\left[-\int_0^a \mu(\hat{a}, h(\hat{a},\hat{t}), M(\hat{t}))d\hat{a}\right]$ is the survival function at (a,t), with $\mu(a,h(a,t),M(t))$ denoting the force of mortality. Following Kuhn et al. (2015), we assume that mortality can be lowered by the consumption of a quantity $h(a,t)$ of health care. In addition, we assume that mortality depends on the state of the medical technology $M(t)$ at time t. More specifically, we assume that the mortality rate $\mu(a,h(a,t),M(t))$ satisfies

$$\begin{aligned}\mu(a,h(a,t),M(t)) &\in (0,\infty) \quad \forall\,(a,t)\,;\\ \mu_h(\cdot) &< 0,\ \mu_{hh}(\cdot) > 0;\\ \mu_h(a,0,M(t)) &= -\infty,\ \mu_h(a,\infty,M(t)) = 0 \quad \forall\,(a,t)\,.\end{aligned}$$

By purchasing health care the representative individual can lower the instantaneous mortality rate and thereby improve survival prospects, but only subject to diminishing returns. In regard to medical technology we assume the following properties

$$\mu_M(\cdot) < 0,\ \mu_{MM}(\cdot) \geq 0,\ \mu_{hM}(\cdot) < 0 \quad \forall\,(a,t)\,.$$

Hence, medical technology contributes towards reductions in mortality ($\mu_M(\cdot) < 0$) with (weakly) decreasing returns. We also assume that for any given positive level of health care, $h(a,t) > 0$, medical technology is raising the effectiveness of the consumption of health care ($\mu_{hM}(a,h(a,t),M(t)) < 0$), which is in line with empirical evidence on the positive relationship between the state of medical technology and the demand for health care (e.g. Cutler and Huckman, 2003; Wong et al., 2012; Roham et al., 2014).

Individuals enjoy period utility $u(c(a,t))$ from consumption $c(a,t)$. Period utility is increasing and concave: $u_c(\cdot) > 0$, $u_{cc}(\cdot) \leq 0$. In addition, we assume the Inada condition $u_c(0) = +\infty$. Individuals maximize the present value of their expected life-cycle utility

$$\max_{c(a,t),h(a,t)} \int_0^{\omega} e^{-\rho a} u(c(a,t))S(a,t)da \tag{1}$$

by choosing a stream of consumption and health care on the interval $[0,\omega]$, with ω denoting the maximal possible age, with $\rho \geq 0$ denoting the rate of time preference, and with $S(a,t)$, defined above, denoting the survival function.

The individual faces as constraints the dynamics of survival and the dynamics of individual assets $k(a,t)$, as described by the system

$$\dot{S}(a,t) = -\mu(a,h(a,t),M(t))S(a,t), \tag{2}$$

$$\begin{aligned}\dot{k}(a,t) &= r(t)\,k(a,t) + l(a)w(t) - c(a,t)\\ &\quad - \phi(a,t)\,p_H(t)h(a,t) - \tau(a,t) + \pi(a,t) + s(t) + d(t)\,,\end{aligned} \tag{3}$$

with the boundary conditions

$$S(0,t_0) = 1, \quad S(\omega,t_0+\omega) = 0, \tag{4}$$

$$k(0,t_0) = k(\omega,t_0+\omega) = 0. \tag{5}$$

Here, (2) describes the reduction of survival according to the force of mortality. While for the sake of simplification we are subsequently referring to $S(a,t)$ as survival, the function may be interpreted as a more general measure of health that is subject to depreciation over the life-course (Chandra and Skinner, 2012; Kuhn et al., 2015). Indeed, (2) not only describes the mortality process but also proxies for the gradual decline in health over the life-course, as is documented by the gradual accumulation of health deficits (Rockwood and Mitnitski, 2007; Dalgaard and Strulik, 2014; Abeliansky and Strulik, 2018). With our focus being on an individual representing a whole cohort, it is plausible to assume that the consumption of health care slows down the decline in health but cannot reverse it.[6] Furthermore, assuming that utility from consumption and utility from good health are multiplicatively separable, one can easily generalize the interpretation of (1) to include not only health-dependent duration of life but also health-dependent quality of life.

According to (3) an individual's stock of assets $k(a,t)$ (i) increases with the return on the current stock, where $r(t)$ denotes the interest rate at time t; (ii) increases with earnings $l(a)w(t)$, where $w(t)$ denotes the wage rate at time t, and where $l(a)$ denotes an individual's effective age-dependent labor supply; (iii) decreases with consumption, the price of consumption goods being normalized to one; (iv) decreases with private health expenditure, $\phi(a,t)\,p_H(t)h(a,t)$, where $p_H(t)$ denotes the price for health care, and where $\phi(a,t)$ denotes an (a,t)-specific rate of coinsurance; (v) decreases with an (a,t)-specific tax, $\tau(a,t)$; (vi) increases with (a,t)-specific benefits $\pi(a,t)$; and increases with (vii) a transfer $s(t)$ by which the government redistributes accidental bequests in a lump-sum fashion and (viii) the individual receipt of dividend payments $d(t)$ from the health care sector. We follow Suen (2009) and Zhao (2014) by considering a setting without an annuity market.[7,8] Finally, we assume that the survival function is bounded between 1 at birth and 0 at the maximum feasible age ω [see (4)], and that individuals enter and leave the life-cycle without assets [see (5)].

Denoting by $B(t-a)$ the size of the birth cohort at $t_0 = t-a$, this cohort has the size

$$N(a,t) = S(a,t)B(t-a)$$

at age a and time t. By aggregating over the age-groups who are alive at time t we obtain the following expressions for the population size,[9] aggregate capital stock, aggregate effective labor supply, aggregate consumption, and aggregate demand for health care, each at time t:

$$\begin{aligned} N(t) &= \int_0^{\omega} N(a,t)da, \\ K(t) &= \int_0^{\omega} k(a,t)N(a,t)da, \\ L(t) &= \int_0^{\omega} l(a)\,N(a,t)da, \\ C(t) &= \int_0^{\omega} c(a,t)N(a,t)da, \qquad (6) \\ H(t) &= \int_0^{\omega} h(a,t)N(a,t)da. \qquad (7) \end{aligned}$$

3.2. Production and health care

The economy consists of a manufacturing sector and a health care sector for both of which we assume the presence of perfect competition in both output and input markets. In the manufacturing sector a final good is produced by employment of capital $K_Y(t)$ and labor $L_Y(t)$ according to a neoclassical production function

$$Y(A_Y(t), K_Y(t), L_Y(t)) = A_Y(t)K_Y(t)^{\alpha}L_Y(t)^{1-\alpha}, \qquad (8)$$

with $A_Y(t)$ measuring total factor productivity in manufacturing. A manufacturer's profit can then be written as

$$V_Y(t) = Y(A_Y(t), K_Y(t), L_Y(t)) - w(t)L_Y(t) - [\delta + r(t)]\,K_Y(t), \qquad (9)$$

where δ denotes the depreciation rate of capital. Note that the presence of perfect competition together with a neoclassical production function in the two sectors implies $V_Y(t) = 0$ in equilibrium.

[6] It might be argued that health status should show up in the mortality function. The key difference this would make in terms of the mechanics of the model is that through its impact on health status the stream of past health care $h(\hat{a})$ with $\hat{a}$ in $[0;a)$ would also have an impact on mortality at age a besides the level of current (acute) health care $h(a)$. This would add a motive for the individual to invest in preventive health care. Given that preventive care, even when defined broadly, accounts only for around 9% of health care expenditure (Miller et al., 2008), we believe these effects to be of second order and, therefore, omit them for the sake of a leaner analysis.

[7] This is well in line with evidence that few individuals annuitize their wealth (e.g. Warshawsky, 1988; Reichling and Smetters, 2015). Hansen and Imrohoroglu (2008) show that the empirically relevant hump-shaped life-cycle profile of consumption can be consistently explained within a life-cycle model only when assuming that annuity markets are assumed to be absent (or severely imperfect).

[8] We have also considered a specification with imperfect annuities yielding a return $r(t) + \xi\overline{\mu}(a,t)$, where $\xi \in [0,1]$ and where $\overline{\mu}(a,t) = \mu(a, h^*(a,t), M(t))$ is the expected mortality, given the equilibrium level of health care $h^*(a,t)$. Following Heijdra and Mierau (2012) in considering a scenario with $\xi = 0.7$, we obtain qualitatively similar results to those reported in this paper.

[9] In a slight abuse of notation, $N(t)$ denotes the population size at time t, whereas $N(a,t)$ represents the size of the cohort aged a at time t.

Consumers purchase health care from providers operating in a health care sector. Here, we assume that at each point in time, the health care sector is made up of a continuum of frontier providers ($j = f$) producing state-of-the art medical output of effectiveness $M^f(t)$, and of a continuum of "common" providers ($j = c$) producing output of effectiveness $M^c(t) < M^f(t)$.

Let $m(t) \in [0,1]$ denote the share of all health care at time t that is produced by frontier providers. In order to keep our model tractable, we assume that the representative individual is unable to distinguish between state-of-the-art and common health care at the point of deciding the optimal quantity $h(a,t)$. Assignments of patients to providers are assumed to be randomized throughout, implying that there is no learning and/or sticking to providers of a certain type over time. Based on the probability $m(t)$ of being assigned to a frontier provider at t, the representative individual then expects to be treated at a technology level

$$M(t) = m(t) M^f(t) + [1 - m(t)] M^c(t). \tag{10}$$

Health care goods and services are produced by both types of providers through the employment of labor $L_H^j(t)$, and capital $K_H^j(t)$, with $j = f, c$ according to a production function

$$F^j(t) = F(A_H(t), K_H^j(t), L_H^j(t)) = A_H(t) \left[K_H^j(t)\right]^{\beta_1} \left[L_H^j(t)\right]^{\beta_2}, \quad j = f, c, \tag{11}$$

where $\beta_1 + \beta_2 \leq 1$ and where $A_H(t)$ measures total factor productivity in health care. In contrast, to the final goods sector, we assume (potentially) decreasing returns to scale within the health care sector.[10]

Note that we are adopting a view on medical innovations as product rather than process innovations. Thus, while innovative health care is associated with a higher marginal impact on mortality, i.e. while $\mu_{hM} < 0$ is true, the production of each unit of care (e.g. each hour of treatment, or each surgery) is unaffected by the level of technology $M^j(t)$, implying that frontier and common providers produce according to the same production technology, $F(\cdot)$.

We assume that innovative health care may be subsidized at a rate $\varphi^f \geq \varphi^c \equiv 0$. For a given price of health care $p_H(t)$, the profit of a type j provider is then given by

$$\begin{aligned} V_H^j(t) = {} & p_H(t) \left(1 + \varphi^j\right) F(A_H(t), K_H^j(t), L_H^j(t)) - w(t) L_H^j(t) \\ & - [\delta + r(t)] K_H^j(t), \quad j = f, c \end{aligned} \tag{12}$$

where we assume that capital depreciates at the same rate across both provider types and both sectors. Given the assumption of decreasing returns we then have $V_H^j(t) \geq 0$ for both types in competitive equilibrium.

Furthermore, the following can be shown [see (46) in Online Appendix A3.2]: In equilibrium, it holds that $F^f(t) > (=) F^c(t)$ if and only if $\varphi^f > (=) 0$.[11] Hence, innovative hospitals tend to (weakly) employ more factors and produce (weakly) greater quantities of output, as is in line with evidence in Skinner and Staiger (2015) and Chandra et al. (2016).[12]

Total output in the health care sector is distributed according to $H(t) = \varrho(t) F^f(t) + [1 - \varrho(t)] F^c(t)$, where $\varrho(t) \in [0,1]$ denotes the share of providers who have adopted the state-of-the-art technology at time t. We then obtain

$$m(t) = \frac{\varrho(t) F^f(t)}{\varrho(t) F^f(t) + [1 - \varrho(t)] F^c(t)} \tag{13}$$

as the share of innovative output. Note that $m(t) \geq \varrho(t)$ if and only if $F^f(t) \geq F^c(t)$.

We complete the description of the health care sector by stating our model of a random diffusion process. Let

$$\varrho(t)_i = \varrho_0 \left[m(t) \frac{H(t)}{N(t)}\right]^{\eta} \varrho_0, \eta > 0 \tag{14}$$

denote the probability that an individual hospital i adopts in period t the frontier technology $M^f(t)$ as opposed to the "common" technology $M^c(t)$. Following the literature on spillovers in respect to the adoption of medical technologies/practice styles (Chandra and Staiger, 2007; Baicker and Chandra, 2010; Li, 2013, 2014; Agha and Molitor, 2018; Molitor, 2018) and taking into account that generally it is market density rather than market size that is conducive to spillovers (Carlino et al., 2007), we assume that this probability increases in the market density of innovative (frontier) care $m(t) \frac{H(t)}{N(t)}$.

[10] In assuming decreasing returns to scale we follow Acemoglu and Finkelstein (2008) who show that the increase in labor costs following the introduction of prospective reimbursement for hospitals has led to a reduction of labor inputs but not of capital inputs. As they argue, this is consistent only with a decreasing returns to scale technology. Decreasing returns to scale imply the presence of quasi-fixed factors at the level of the individual provider and, more importantly in our case, at the sectoral level. Bilodeau et al. (2000, 2004) and Ouellette and Vierstraete (2004) show that quasi-fix physician supply and capital in the hospital sector lead to a deviation from long-run cost minimization at the hospital level and to decreasing returns and a failure for productivity change to trigger cost savings at the sectoral level. In addition, Cremieux et al. (2005) show that lacking flexibility in the adjustment of certain bottleneck outcomes implies that cost grows with demand in both private and public hospital markets. They also show that these rigidities are aggravated by technological progress. We thus believe our assumption of decreasing returns to be well founded.

[11] Note that an asymmetric equilibrium with both providers being active for $\varphi^f > 0$ exists only if $\beta_1 + \beta_2 < 1$. It is sufficient here to assume a relatively small deviation from the constant returns assumption.

[12] We assume the absence of subsidies, i.e. $\varphi^f = 0$, in our benchmark scenario, developed in Section 6.2; in the counterfactual (i) without medical progress (see Section 7.1); and in the counterfactual (ii) with perfect diffusion (see Section 7.2). We assume $\varphi^f > 0$ in counterfactual (iii) on the subsidization of frontier health care (see Section 7.3).

Given we are considering ex-ante symmetric hospitals, we have $\varrho(t)_i = \varrho(t)$ in equilibrium. Thus, substituting from (13) we can solve the equilibrium relationship $\varrho(t) = \varrho_0 \left[m(t) \frac{H(t)}{N(t)} \right]^{\eta}$ for $\varrho(t)$ as a function of $\left\{ F^f(t), F^c(t), \frac{H(t)}{N(t)} \right\}$. In order to guarantee that $\varrho(t) \leq 1$ we need to assume that $\varrho_0 \left[\frac{H(t)}{N(t)} \right]^{\eta} \leq 1$. It can then be shown that there is a unique equilibrium value $\varrho(t)$ (see Online Appendix A1).

Finally, following Skinner and Staiger (2015) who adopt a model of diffusion in the spirit of Nelson and Phelps (1966), we formulate the change in "common" medical technology as

$$\dot{M}^c(t) = \varrho(t) \left[M^f(t) - M^c(t) \right], \tag{15}$$

with the frontier technology $M^f(t)$, in turn, following an exogenous growth path. Thus, the stock of the common medical technology is advanced toward the medical frontier according to the diffusion rate $\varrho(t)$.

At this point, let us issue the following caveat. While in the light of the evidence reviewed in Section 2 the notion that medical progress arises from knowledge spillovers in the process of health care production is a plausible reduced form formulation, our model abstracts from the notion that ultimately the adoption of new (frontier) medical technology is the outcome of deliberate profit-maximizing choices on the part of health care providers. For this reason, we present in the Online Appendix B a variant of the model that builds on profit-maximizing adoption decisions on the part of hospitals, a route that has also been taken by Skinner and Staiger (2015) albeit in a somewhat different setting. We show how the equilibrium diffusion rate $\varrho(t)$ arises as a function of market value $p_H(t) H(t)$ and a measure of competitive advantage for adopters of the frontier technology. We go on to argue that while upon proper calibration the model with endogenous adoption choices is unlikely to generate vastly different results, it is likely to prove numerically intractable. Given this, we continue to pursue the reduced form version with a view to keeping the model and its numerical implementation tractable.

3.3. Transfers and taxes

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 $1 - \phi(a,t)$ and of paying out transfer payments $\pi(a,t)$. More specifically, where $\pi(a,t)$ refers to pension benefits we have

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

with $\hat{\pi}(t)$ being a uniform time-dependent pension benefit and a_R the retirement age. In such a setting we also have

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

Assuming that the government budget must be balanced within each period t we obtain the constraint

$$\int_0^{\omega} \left\{ \begin{array}{c} [1 - \phi(a,t)] p_H(t) h(a,t) \\ + \pi(a,t) - \tau(a,t) \end{array} \right\} N(a,t) da = 0, \tag{16}$$

where $\tau(a,t)$ denotes an age-specific tax. We will determine the precise structure of the tax system in the course of the model calibration in Section 6.1.

Finally, we assume the lump-sum redistribution of accidental bequests and the profits within the health care sector such that

$$s(t) = \frac{Y_B(t)}{N(t)}, \tag{17}$$

where

$$Y_B(t) = \int_0^{\omega} \mu(a,t) k(a,t) N(a,t) da \tag{18}$$

are total accidental bequests,[13] and

$$d(t) = \frac{\varrho(t) V_H^f(t) + [1 - \varrho(t)] V_H^c(t)}{N(t)}, \tag{19}$$

where $\varrho(t) V_H^f(t) + [1 - \varrho(t)] V_H^c(t)$ is the total profit in the health care sector.

[13] In order to ease on notation, we will subsequently refer to the shortcut $\mu(a,t)$ for $\mu(a, h(a,t), M(t))$.

4. Life-cycle optimum

In Online Appendix A2 we show that the solution to the individual life-cycle problem is given by the following two sets of conditions

$$\frac{u_c\left(c\left(a,t\right)\right)}{\exp\left\{-\int_a^{\hat{a}}\left[\rho+\mu\left(\hat{\hat{a}},t+\hat{\hat{a}}-a\right)\right]d\hat{\hat{a}}\right\}u_c\left(c\left(\hat{a},t+\hat{a}-a\right)\right)} = \exp\left[\int_a^{\hat{a}} r\left(t+\hat{\hat{a}}-a\right)d\hat{\hat{a}}\right], \tag{20}$$

$$\psi\left(a,t\right) = \frac{\phi\left(a,t\right)p_H\left(t\right)}{-\mu_h\left(a,t\right)} \quad \forall\left(a,t\right), \tag{21}$$

describing the optimal pattern of consumption $c\left(a,t\right)$ and the demand for health care $h\left(a,t\right)$, respectively, of an individual aged a at time t. Condition (20) is the well-known Euler equation, requiring that the marginal rate of intertemporal substitution between consumption at any two ages/years $\left(a,t\right)$ and $\left(\hat{a},t+\hat{a}-a\right)$ equals the compound interest. Note that in the absence of annuity markets the uninsured mortality risk can be interpreted as an additional factor of discounting, implying an effective discount rate $\rho+\mu\left(a,t\right)$ at any $\left(a,t\right)$. Rising mortality then imposes a downward drag on consumption toward the end of life.

Condition (21) requires that at each $\left(a,t\right)$ the private value of life, i.e. the willingness to pay for survival, $\psi\left(a,t\right)$, equals the price of survival, $-\phi\left(a,t\right)p_H\left(t\right)/\mu_h\left(a,t\right)$. Here, the consumer price for health care, $\phi\left(a,t\right)p_H\left(t\right)$, is converted into a price of survival by weighting with the number of units of health care required for a unit reduction in mortality, $\left[\mu_h\left(a,t\right)\right]^{-1}$. The private value of life is defined by

$$\psi\left(a,t\right) := \int_a^{\omega} v\left(\hat{a},t+\hat{a}-a\right)R\left(\hat{a},a\right)d\hat{a}, \tag{22}$$

with

$$v\left(a,t\right) := \frac{u(c\left(a,t\right))}{u_c\left(\cdot\right)}, \tag{23}$$

and

$$R\left(\hat{a},a\right) := \exp\left[-\int_a^{\hat{a}} r\left(t+\hat{\hat{a}}-a\right)d\hat{\hat{a}}\right], \tag{24}$$

and amounts to the discounted stream of consumer surplus, $v=u\left(\cdot\right)/u_c\left(\cdot\right)$ taken over the expected remaining life-course $[a,\omega]$.[14] It is readily checked that the value of life at each $\left(a,t\right)$ increases (i) with the level of the individual's consumption and, thus, the individual's income, and (ii) with the state of the medical technology, the latter effect arising as technology-induced mortality reductions, $\mu_M\left(\hat{a},t+\hat{a}-a\right)<0$, cause over the remaining life-course $\hat{a}\in\left(a,\omega\right)$ a reallocation of consumption toward these later life-years. The price of survival $\left(a,t\right)$, in turn, decreases (i) with health insurance coverage, $1-\phi\left(a,t\right)$, at $\left(a,t\right)$, and (ii) with the state of the medical technology, given that the latter raises the effectiveness of health care, $\mu_{hM}\left(a,t\right)<0$. Thus, the demand for medical care will – ceteris paribus – increase with income, with the extent of health insurance, and, in particular, with the state of the medical technology.

5. General equilibrium

Perfectly competitive firms in the production sector choose labor $L_Y(t)$ and capital $K_Y\left(t\right)$ so as to maximize period profit (9). The first-order conditions imply

$$r\left(t\right) = Y_{K_Y}\left(t\right)-\delta, \tag{25}$$

$$w\left(t\right) = Y_{L_Y}\left(t\right), \tag{26}$$

i.e. the factor prices are equalized with their respective marginal products.

Likewise, perfectly competitive providers of health care choose labor $L_H^j(t)$ and capital $K_H^j\left(t\right)$, $j=f,c$, so as to maximize period profit (12). From the first-order condition we obtain

$$r\left(t\right) = p_H\left(t\right)\left(1+\varphi^j\right)F_{K_H^j}\left(t\right)-\delta, \tag{27}$$

$$w\left(t\right) = p_H\left(t\right)\left(1+\varphi^j\right)F_{L_H^j}\left(t\right). \tag{28}$$

[14] The value of life (VOL) as we calculate it here differs from the typical representation of the value of a statistical life as e.g. in Murphy and Topel (2006) in as far as (i) the discount factor does not include the mortality rate; and (ii) the VOL does not include the current change to the individual's wealth, $lw-c-h-\tau+\pi+s+d$. Both of these features are due to the absence of an annuity market.

Combining these conditions with (25) and (26) we obtain

$$\left(1+\varphi^{j}\right) p_H(t) = \frac{Y_{L_Y}(t)}{F_{L_H^j}(t)} = \frac{Y_{K_Y}(t)}{F_{K_H^j}(t)}, \tag{29}$$

implying that capital and labor inputs are distributed across the production and health care sector in a way that equalizes the marginal rate of transformation (i.e. the relative output gain in production as compared to the output loss in health care from re-allocating one factor unit from health care into production) with the price for health care. The higher the latter, the greater the marginal rate of transformation, implying that more workers will be allocated to the health care sector. With appropriate Inada conditions, $Y_{L_Y}(K_Y,0) = Y_{K_Y}(0,L_Y) = \infty$ and $F_{L_H^j}(K_H^j,0) = F_{K_H^j}(0,L_H^j) = \infty$ we always have an interior allocation with $L_Y(t) = L(t) - \varrho(t) L_H^f(t) - [1-\varrho(t)] L_H^c(t) \in (0, L(t))$ and $K_Y(t) = K(t) - \varrho(t) K_H^f(t) - [1-\varrho(t)] K_H^c(t) \in (0, K(t))$.

Our setting involves four markets: two input markets for capital and labor, respectively; and two output markets for health care and for final goods, respectively. From the four market clearing conditions

$$\begin{aligned} K_Y(t) + \varrho(t) K_H^f(t) + [1-\varrho(t)] K_H^c(t) &= K(t), \\ L_Y(t) + \varrho(t) L_H^f(t) + [1-\varrho(t)] L_H^c(t) &= L(t), \\ \varrho(t) F^f(t) + [1-\varrho(t)] F^c(t) &= H(t), \\ Y(t) &= C(t) + \dot{K}(t) + \delta K(t), \end{aligned}$$

we obtain a set of equilibrium prices $\left\{r^*(t), w^*(t), p_H^*(t)\right\}$ as well as the level of net capital accumulation $\dot{K}(t)$. We provide a more detailed description of the general equilibrium structure as well as a representation for Cobb–Douglas production functions in Online Appendix A3.

6. Numerical analysis

In this section, we set out a description of the numerical analysis, involving details on the calibration of our model. Subsequently, we present the outcomes for the benchmark scenario which reflects the salient features of the US demographic and economic development over the time span 1970–2005. In Section 7 we will compare against this benchmark the outcomes for a series of counterfactual scenarios, each rolled out over the time span 1980–2005, i.e. covering the cardiac revolution, which will afford us insights about the impact of medical progress on economic performance and welfare as well as about the role of the diffusion process. Technical information on the numerical solution method is provided in Online Appendix A4.

6.1. Specification of the numerical analysis

Demography

Individuals enter the model economy at age 20 and can reach a maximum age of 100 with model time progressing in single years.[15] 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 fixed growth rate schedule of "births" $\nu(t)$. The number of births at time t is given by

$$B(t) = B_0 \exp\left[\int_0^t \nu(\hat{t}) d\hat{t}\right], B_0 > 0.$$

The time-dependence of the growth rate of births will be set (in consideration of endogenous mortality) to match the age-structure of the United States in 1980 and 2000 (see Table 2).[16] Due to the exogenous path of births, our results will not be driven by changing birth numbers across the experiments. This notwithstanding, with the bulk of mortality lying beyond the fecund years since the second half of the 20th century, we do not expect the assumption of an exogenous flow of births to have any great impact on our results.

Mortality

The force of mortality $\mu(a,t) = \mu(h(a,t), M(t))$ is endogenously determined in the model and depends on health care, $h(a,t)$, as a decision variable, and on the expected level of medical technology, $M(t)$. Adapting Hall and Jones (2007), we formulate

$$\mu(a,t) = \theta(a,t) (h(a,t))^{\kappa(a) M(t)}, \tag{30}$$

where $\theta(a,t) > 0$ and $\kappa(a) < 0$ are parametric functions that reflect the age-specific effectiveness of health care, and where the expected level of medical technology is given by (10).[17,18] Here, the elasticity $\kappa(a) M(t)$ should be read as a measure of the (medical)

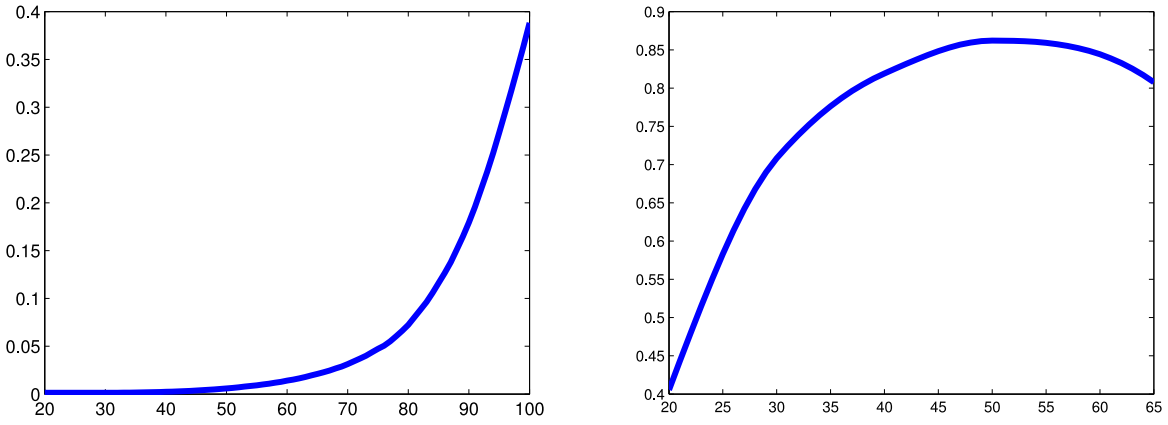
[15] We follow the bulk of the literature and neglect life-cycle decisions during childhood.

[16] Note that our primary measures of age-structure, namely the population share of individuals aged 65 or older, as well as the employment-population ratio refer to the population aged 20 or older in the denominator. The data used in Table 2 hence refers to the population without individuals aged less than 20.

[17] The functional form of $\mu(a,t)$ fulfills the properties of the mortality function outlined in Section 3.1 within the relevant value space of h, κ and M.

[18] Strictly speaking, the representative individual would base its decision on the expected mortality, as given by

$$\mu(a,t) = m(t)\theta(a,t) h^{\kappa(a) M^f(t)} + [1-m(t)]\, \theta(a,t) h^{\kappa(a) M^c(t)},$$



(a) US 1980 force of mortality (HMD) (b) Age-specific labor employment schedule

Fig. 1. Mortality and labor employment age-profiles.

effectiveness of one unit of health care in lowering mortality. As is evidenced by e.g. Hall and Jones (2007) this effectiveness varies with age. Intuitively, one would also expect it to depend on the state of the medical technology. While we cannot quote direct evidence on the impact of medical progress on medical effectiveness, Gallet and Doucouliagos (2017) provide evidence from a meta-regression analysis that the elasticity of mortality with respect to health spending (in absolute terms) increases over time, evidence that is tantamount to the presence of medical progress.[19] Note that this feature of medical progress can only be captured if $M(t)$ is, indeed, part of the elasticity of health care utilization, $h(a,t)$, rather than part of a mortality shifter, such as $\theta(a,t)$.

We choose $\kappa(a)M(t=2000)$ to be in the range of age-specific elasticities of mortality with respect to health care utilization for the year 2000, as reported in Hall and Jones (2007). The age-component of the term $\theta(a,t)$ is then determined such that the age pattern of optimal health expenditure and the endogenous level of medical technology yield the empirically observed mortality pattern for a given year.[20]

From the OECD (2018) data on causes of death one can glance that around 65% of the decline in mortality over the time span 1980–2005 can be attributed to declines in the mortality from coronary (or ischemic) heart disease. Combining this information with the insight from Ford et al. (2006) that around 50% of the mortality decline in coronary heart disease was attributable to changes in medical treatment, we attribute 32.5% of the change in mortality over the time span 1980–2005 to changes in $h(a,t)$ and $M(t)$. We thus assume $\theta(a,t)$ to follow a negative time-trend that explains the 67.5% of the overall 1980–2005 decline in mortality that are not attributable to medical treatments.

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 $\sigma = 1.2$ which is within the range of the empirically consistent values suggested by Chetty (2006). Setting $b = 17$ then guarantees that $u(a,t) \geq 0$ throughout and generates an average value of life that lies within the range of plausible estimates, as suggested in Viscusi and Aldy (2003) and documented in Table 2. Moreover, we assume a rate of time preference $\rho = 0.03$.

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where $m(t)$ denotes the probability of receiving a state-of-the-art treatment (or equivalently, the share of patients receiving state-of-the-art treatment). The problem with the expected mortality formulation is that it is difficult to implement in our numerical analysis. Having verified that for our calibration the expected mortality is approximated almost perfectly by the formulation in (30), we resort to employing the latter.

[19] The findings by Gallet and Doucouliagos (2017) can be read as longitudinal evidence for medical progress as a driver of medical effectiveness. When considering specific NHS treatment programs for cancer and circulatory disease, Martin et al. (2008) report spending elasticities (in respect to mortality) that are much higher than the ones reported in Hall and Jones (2007). Given that the technologies considered in Martin et al. (2008) are focused on mitigating mortality whereas Hall and Jones (2007) consider all health care, the discrepancy in the estimated elasticities can be interpreted as cross-sectional evidence for technology as a determinant of medical effectiveness.

[20] We use the year 1980, representing the beginning of the cardiac revolution, to calibrate $\theta(a)$. The mortality rate for the US in 1980, as plotted in Fig. 1(a), is taken from the Human Mortality Database.

Finally, we impose a minimum consumption level equal to the social security benefit at a given point in time. We do so to avoid negative asset holdings at old age, as would otherwise result from ex-ante optimization.[21] Given that retirees cannot usually borrow 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.

Effective labor supply and income

We proxy the effective supply of labor $\widehat{l}(a)$ by an age-specific income schedule (see Fig. 1(b)), constructed from 2003 earnings data, as contained in the Current Population Survey (CPS) provided by the Bureau of Labor Statistics (BLS). We rescale the schedule such that the employment-population ratio $L(t)/N(t)$ matches the empirical value of 62% for the US in 2003 as reported by the BLS. Individuals aged 65 or older are assumed to have no labor income but receive a fixed social security pension for the remainder of their lifetime, as detailed further on below.

Production and health care

For final goods production, as described by the neoclassical production function (8), we assume a capital elasticity $\alpha = 1/3$. The exogenous technology index $A_Y(t)$ is calibrated so that $l(50)w(t)$ matches the average earnings of a 50-year old in 2003 and assumed to grow at a rate of 1.5% per year, such that GDP per capita is growing in line with the data.[22]

For the production of health care, as described by (11), we assume a capital elasticity $\beta_1 = 0.2$, employing an estimate from Acemoglu and Guerrieri (2008). We then choose $\beta_2 = 0.7$, which generates an employment share of the health care sector that is broadly in line with the literature.[23] Total factor productivity, $A_H(t)$, is assumed to grow at a rate of 0.5%, reflecting slow productivity growth within the health care sector.[24] Finally, we assume a rate of capital depreciation equal to $\delta = 0.05$.

For the benchmark scenario in Section 6.2 and for our counterfactual scenarios covering the absence of medical progress [counterfactual (i) in Section 7.1] and full diffusion of medical progress [counterfactual (ii) in Section 7.2] we assume the absence of subsidies, such that $\varphi^f = \varphi^c \equiv 0$. As we have shown in Section 3.2, this implies $F^f(t) = F^c(t)$. Frontier and common providers are then symmetric in respect to their input choices, output levels and profits.[25] Furthermore, as is readily verified from (13) the share of frontier output in the benchmark is then given by $m(t) = \varrho(t)$. For this case, we can explicitly determine the equilibrium diffusion rate

$$\varrho(t) = \varrho_0 \left[\frac{H(t)}{N(t)}\right]^{\frac{1}{1-\eta}}. \tag{31}$$

While there is mounting evidence on knowledge-spillovers and agglomeration effects as drivers of innovation and technology diffusion in the health care context (for references see the discussion in Section 2), we were unable to identify from the literature measures that would allow us to quantify the elasticity η or, equivalently, the elasticity $\frac{1}{1-\eta}$. We therefore draw on more general evidence on diffusion processes. Comin and Mestieri (2014) provide evidence for a set of different technologies on how the speed (or rate) of diffusion depends on aggregate demand (see also Comin, 2009; Comin and Mestieri, 2010). Filtering out seasonal trends, they find that the long-run trend of GDP (as measure of demand) is related to the speed of diffusion by an elasticity of around 2.2. Taking a conservative stance, we thus assume that $\frac{1}{1-\eta} = 2$, implying that $\eta = 0.5$.[26] Finally, we choose ϱ_0 in a way that the diffusion rate $\varrho(t)$ in the year $t = 1995$ equals 0.075, a value that corresponds to the average diffusion rate found in the empirical analysis by Skinner and Staiger (2015).[27]

In our calibration we seek to match the increase in health expenditures and the health expenditure share of GDP, the data on which is taken from the National Health Expenditure Tables provided by the National Health Accounts (NHA).[28] Furthermore, we aim to match the increase in life-expectancy observed between 1980 and 2005, of which only 32.5% should be directly explained by increases in technology and health care utilization. Thus, in a first step we impose a time-trend on $\theta(a,t)$ such that in the

[21] 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.

[22] Here, we employ the "Real gross domestic product per capita", as provided by the Federal Reserve Bank of St. Louis. Note, however, that $A_Y(t)$ does not determine GDP per capita growth alone, with the evolution of demography, medical technology, health expenditures and other factors also playing a role.

[23] We find for 1995 an employment share of 12.5% which is reasonably close to the 8.5% reported by Pauly and Saxena (2012).

[24] This choice of value is in line with Faere et al. (1997) and Spitalnic et al. (2016) who measure productivity growth in the US health care sector based on the quantity rather than the quality of services and find average productivity growth rates of 0.1–0.7%. While medical progress in the sense of better health and mortality outcomes is measured by $M(t)$, the measure of increased quantity-related productivity is a good proxy for A_H.

[25] This is consistent with our assumption that the consumer is unable to distinguish/choose between frontier and common care at the point of purchase (e.g. Skinner and Staiger, 2015). As both types of care command the same market price p_H and providers face the same technology, frontier providers do not benefit financially.

[26] While the estimates by Comin (2009) and Comin and Mestieri (2010) refer to total GDP rather than to GDP per capita, it is easy to check that for our functional formulation the adjustment for population size has no bearing on the relevant elasticity.

[27] While Skinner and Staiger (2015) do not directly report a diffusion rate, it can be calculated as follows: In their Table 1, Skinner and Staiger (2015) report that by 1995 a fraction of 0.8 of all hospitals had adopted the use of aspirin as one innovative therapy in the treatment of acute myocardial infarction. They also report in their Footnote 13 that aspirin was first adopted in 1975, implying a 20 year time horizon. Solving the diffusion equation $0.8 = 1 - (1 - \varrho)^{20}$ gives $\varrho = 0.077$. Similar values are obtained for the use of beta blockers and the use of reperfusion within 12 h as additional markers of innovative coronary treatments.

[28] All dollar values are to be understood as constant 2009 USD.

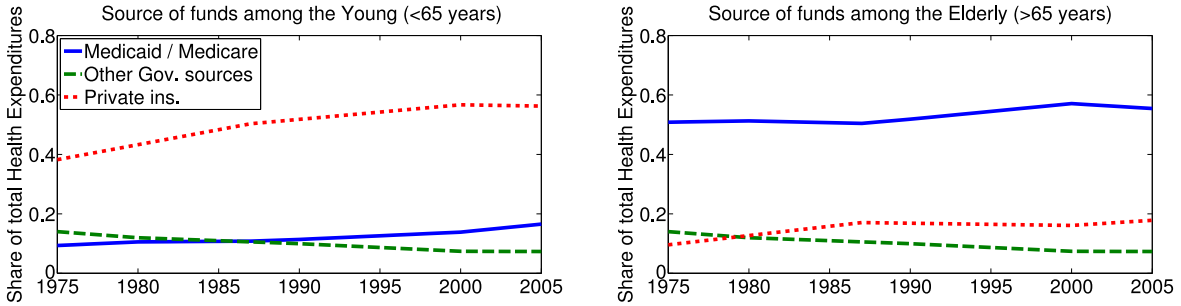

Fig. 2. Share of total health expenditures over time covered by Medicaid (for the young) and Medicare (for the elderly), by other government programs, and by private insurance for the young (left) and for the elderly (right).

absence of any growth in health care utilization and medical progress $\theta(a,t)$ itself can explain 67.5% of the observed increase in life expectancy.[29] In a second step, we choose the growth path of $M^f(t)$ such that, in combination with the diffusion rate $\varrho(t)$ according to (15), it generates a time path for $M^e(t)$ and an expected state of medical technology (10) which (together with the implied level of health care utilization) explain the remaining 32.5%. Finally, we move the utility parameter b which governs the magnitude of the value of life to adjust health care expenditures to the level observed in the data. Adjusting b requires a readjustment in the growth path of $M^f(t)$ and $\theta(a,t)$ such that these parametric choices have to be made in an iterative procedure.

Health insurance, medicare and social security

Health expenditures are subsidized through private health insurance with coinsurance rate $\phi_P(a,t)$, and through public insurance provided by Medicare, Medicaid and other public programs. We assume that Medicare is only available to the elderly (after the mandatory retirement age $a_R = 65$) with coinsurance rate $\phi_{MC}(a,t)$ and Medicaid only to those of working age ($a < a_R$) with a coinsurance rate $\phi_{MA}(a,t)$. The remaining public programs are assumed to be available to all age-groups at a coinsurance rate $\phi_{RP}(a,t)$. We use data on health insurance coverage in the US from the National Center for Health Statistics (NCHS). The NCHS reports sources of payments for health care among the young (<65 years old) and the elderly, providing information on the proportions of total health expenditures that were paid for out-of-pocket (OOP) and through private insurance, Medicare, Medicaid and other public insurance programs, respectively.[30]

Fig. 2 shows the evolution of insurance coverage from 1975 to 2005 for the young (<65 years) and for the elderly in the US. In our simulation, we interpret the shares of each type of fund as exogenous age- and time-dependent health care subsidies.

Private health insurance is financed through a "risk-adequate" premium equal to the expected health expenditure, $p_H(t)h^*(a,t)$, covered by the insurance for an individual at a given time and age. It is thus given by $\tau_P = \left[1-\phi_P(a,t)\right] p_H(t)h^*(a,t)$. As described above, we set $\phi_P(a,t)$ equal to the share of expenditures paid for by private insurance, where we obtain different co-payment rates among the young and the elderly in accordance with the data. Analogously, we can construct $\phi_{MC}(a,t)$, $\phi_{MA}(a,t)$ and $\phi_{RP}(a,t)$.[31] All public programs are financed through payroll taxes, with the rates $\hat{\tau}_{MC}$, $\hat{\tau}_{MA}$ and $\hat{\tau}_{RP}$ being endogenously determined such that the budget constraints

$$\int_{a_R}^{\omega} \left[1-\phi_{MC}(a,t)\right] p_H(t)\, h(a,t)N(a,t)da = \hat{\tau}_{MC}(t)w(t)L(t),$$
$$\int_{0}^{a_R} \left[1-\phi_{MA}(a,t)\right] p_H(t)\, h(a,t)N(a,t)da = \hat{\tau}_{MA}(t)w(t)L(t),$$
$$\int_{0}^{\omega} \left[1-\phi_{RP}(a,t)\right] p_H(t)\, h(a,t)N(a,t)da = \hat{\tau}_{RP}(t)w(t)L(t)$$

hold, where $1-\phi_x(a,t)$ is the share of health expenditures paid by program $x = MC, MA, RP$.

Social security is financed through a payroll tax at rate $\hat{\tau}_{II}$ which is determined endogenously from the social security budget constraint

$$\int_{a_R}^{\omega} \hat{\pi}(t)N(a,t)da = \hat{\tau}_{II}(t)w(t)L(t),$$

[29] More specifically, we split $\theta(a,t)$ into two components, such that $\theta(a,t) = \theta^1(a)\theta^2(t)$. We have explained above how $\theta^2(t)$ is calibrated. The parametric function $\theta^1(a)$ is used to match the age-specific mortality rates in the year 1980, as provided by the Human Mortality Database. Thus, for any selection $\{b, \theta^2(t), M^f(t)\}$ we update $\theta^1(a)$ to obtain the age-specific mortality rates in line with the data.

[30] We use the 1976–1977 "Health" report by the NCHS (Table 149) to obtain data from 1966 to 1975, as well as the 2015 "Health" report (Table 98) for the years 1987, 1997, 2000 and 2012 to identify the share of health expenditures funded out-of-pocket, by public programs and by private health insurance for the young and the elderly (65 and above), respectively. We then identify the share of government funds devoted to programs other than Medicare and Medicaid from the 2010 "Health" report (Table 126) for 1960–2006. Based on this data and under the simplifying assumption that Medicaid is utilized only by the young and Medicare only by the elderly, we can construct the time-series in Fig. 2. All NCHS "Health" reports are available at https://www.cdc.gov/nchs/hus/previous.htm.

[31] The age-specific total co-insurance rate of health expenditures exhibits a small discontinuity at age 65 when using this calibration strategy. We smooth the jump after retirement by linearly adjusting the private insurance levels of individuals after retirement.

Table 1
Model parameters.

Parameter & functional forms	Description
$\omega = 80$	Life span
$t_0 = 1950$	Entry time of focal cohort
$\rho = 0.03$	Pure rate of time preference
$\sigma = 1.2$	Inverse elasticity of intertemporal substitution
$b = 17$	Constant utility of being alive
$a_R = 65$	Mandatory retirement age
$\delta = 0.05$	Rate of depreciation
$\alpha = 0.33$	Elasticity of capital in Y
$\beta_1 = 0.2$	Elasticity of capital in F
$\beta_2 = 0.7$	Elasticity of labor in F

Table 2
Targets to match.

Parameter	Target	Match
$\theta(a,t)$	Mortality profile	Perfect match for 1980 by construction Match for other years see life-expectancy
$M(t)$	Life-expectancy at birth	Model: 75.3 (1980), 77.8 (2000) Data: 75.3 (1980), 77.9 (2000) see also Fig. 5
$\nu(t)$	Share of Elderly	Model: 16.5% (1980), 17.9% (2000) Data: 16.6% (1980), 17.3% (2000)
σ	Income elasticity of health care spending	0.9 (over period 1980 to 2005)
b	Value of life Health exp. capita / share of GDP	Model: 5.4 Mio. (1980), 8.6 Mio. (2000) Data: 7 Mio (2000) see Fig. 3
$\hat{l}(a)$	Income schedule Employment-population ratio	Perfect match by construction 2000: Model: 62.5%, Data: 62.0%
$A_Y(t)$	GDP per capita	see Fig. 3
$\varrho(t)$	Rate of Diffusion Time lag of diffusion	Perfect match for 1995 by construction Model: 8.9 years in 1995 Data: 5–10 years in 1995 (Skinner and Staiger)

where $\hat{\pi}(t)$ is the social security pension. We assume social security benefits to be exogenous and use the Annual Statistical Supplement provided by the Social Security Agency to obtain the average monthly social security income for the years 1970–2005.

Overview of functional forms and parameters

Table 1 summarizes the most important parameters we are employing. Table 2 provides an overview on the calibration strategy and presents the match of several key target variables.[32]

6.2. Benchmark

In this section, we present the benchmark economy over the period 1970–2005 and illustrate the model fit. The benchmark allocation is depicted by blue, solid plots throughout all figures. We confine our presentation to the macroeconomy. Detail on the individual life-cycle outcomes is contained in Online Appendix A5.

Fig. 3 plots the evolution of the GDP, health expenditures per capita and the health expenditure share in GDP against the US data, as depicted by the asterisks. Reasonably well in line with the data, GDP per capita increases by a factor of about 2.25 and health expenditures by a factor of 6 over the time span 1970–2005.[33] The two developments imply an about 2.7-fold increase of the health expenditure share of GDP over the 35 years under consideration.

While the increase in GDP is predominantly driven by the exogenous growth of total factor productivity in the production sector, the increase in health expenditures is driven by several trends: insurance expansion, the expansion in social security and productivity-driven income growth, as well as by medical progress.

[32] We also calculate the elasticities of health care spending with respect to price/insurance and with respect to income as they are implied by our calibration. For the price elasticity we obtain a value of −0.6, which is well in line with estimates by Eichner (1998) and Fonseca et al. (2020). For the income elasticity we obtain a value of 0.9 which is close to the range of values identified by Acemoglu et al. (2013).

[33] We overestimate health expenditure growth in the 1990s. In this period, health maintenance organizations caused a temporary slowdown of expenditure growth (Chernew and Newhouse, 2012), a development that is not tracked well in our model.

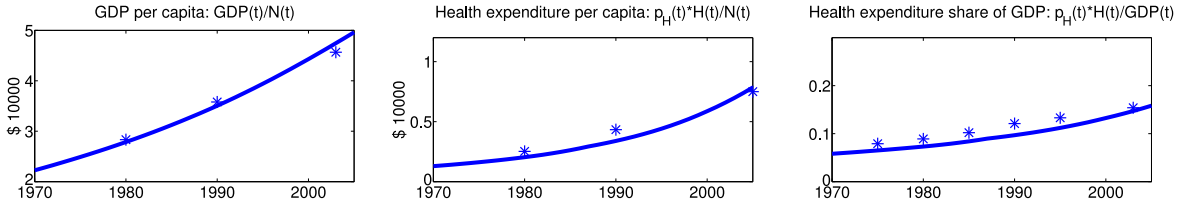

Fig. 3. GDP, health expenditures per capita and GDP share of health expenditure in the benchmark scenario (blue, solid line) and data (asterisks).

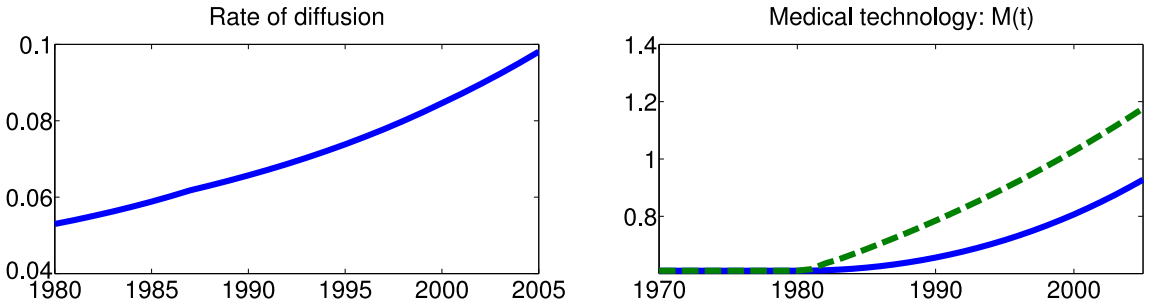

Fig. 4. Rate of diffusion (blue, solid line); and common state (blue, solid line) vs. frontier state (green, dashed) of medical technology in the benchmark.

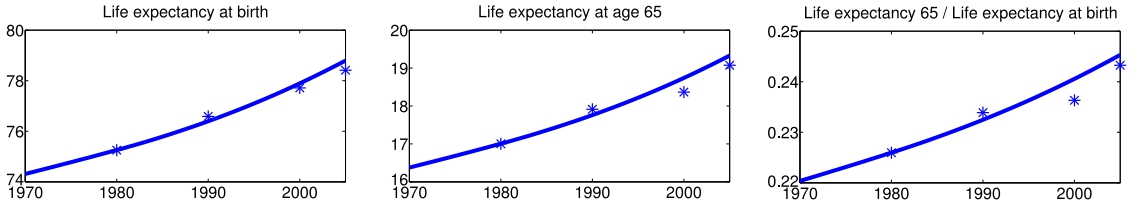

Fig. 5. Life expectancy at birth, life expectancy at age 65, and ratio (LE at 65/LE at birth) in the benchmark (blue, solid line) and data (asterisks).

Fig. 4 illustrates the process that is governing medical innovations during the cardiac revolution. The left panel plots the rate of diffusion $\varrho(t)$ as it emerges endogenously. By inducing additional knowledge spillovers the increase in market density, as measured by the per capita demand for health care, H/N, intensifies diffusion over time. In accordance with the elasticity $\frac{1}{1-\eta} = 2$ driving such market density effects, $\varrho(t)$ grows over the time span 1980–2005 at a rate of 2.5%. Despite the resulting increase in the diffusion rate from 5.3% in 1980 to 9.75% in 2005, this still implies a relatively slow speed of diffusion, as documented by Skinner and Staiger (2015) for health care and by Comin and Mestieri (2014) more generally. Recall that we have calibrated the growth path of the frontier state of medical technology $M^f(t)$ such that together with the diffusion process it matches the development of life expectancy and per capita health expenditure in the data. The right panel of Fig. 4 then plots the trajectory of the common state of medical technology $M^c(t)$ against the frontier $M^f(t)$. In line with the OECD (2018) data on ischemic mortality, both measures are taking off with the cardiac revolution from 1980 onward, with the imperfection of diffusion leaving a sizeable gap between the commonly available technology and the state-of-the art. One good way to assess the size of the gap is to consider the time it takes for the state-of the-art technology, as measured by $M^f(t)$, to have fully turned into the common technology, as measured by $M^c(t)$. Inspection of Fig. 4 shows, for instance, that it takes 8.9 years for the 1995 state-of-the-art technology to be fully adopted. A similar adoption lag applies for the diffusion process throughout, and this is well in line with the time lag of 5–10 years between the fastest and slowest adopters of medical innovations that is reported by Skinner and Staiger (2015).

As a result of the endogenous progress in the reduction of cardiac mortality combined with the exogenous trend, life expectancy rises well in line with the empirical data from a little over 75 years in 1980 to a little under 79 years in 2005. This is illustrated by the left panel of Fig. 5, while the middle and right panels show that the increase in life expectancy is concentrated among the population 65 and above.

The macroeconomic development is well summarized in the price paths depicted in Fig. 6 Here, the interest rate, $r(t)$, which is endogenously determined within the model, falls over the time span 1970–2005 with an acceleration over the period of the cardiac revolution. While we cannot explain the empirical ups and downs of real returns on capital, we can account for the long-term increase in saving and the consequential decline in the interest rate associated with an aging population (see e.g. Bloom et al., 2007; De Nardi et al., 2010; Aksoy et al., 2019).

While boosting the supply of capital through the increase in longevity, medical progress also lowers the demand for capital by shifting production into the comparatively labor-intensive health care sector. The resulting excess supply of capital is, thus, absorbed

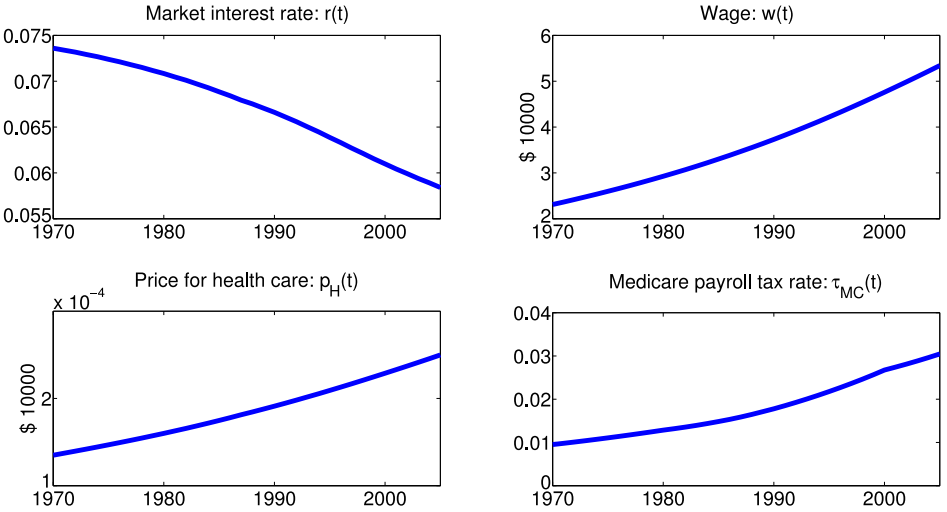

Fig. 6. Prices in the benchmark scenario.

only through a fall in the interest rate. This trend is further reinforced by the well-known Baumol (1967) effect, where productivity growth in the capital-intensive final goods sector induces a shift of production factors into the more labor-intensive health care sector. The ensuing (relative) scarcity of labor tends to depress the interest rate even further.[34]

Wage growth mainly reflects the increase in productivity, but wages also rise due to the increasing relative scarcity of labor as described above. As the health care sector is comparatively labor-intensive, the rising price for labor overcompensates the falling price for capital and induces the price of health care to grow over time. We can compare p_H with the ratio of the medical price index to the consumption price index (CPI) in the US, as based on data from the Bureau of Economic Analysis (BEA). Over the time span 1980–2005, medical prices have risen 1.8-times faster than the overall CPI according to BEA, which is what we obtain for the increase in p_H over the same time span.

Finally, the bottom right panel of Fig. 6 depicts the development of the implicit Medicare tax rate, which increases by a factor of 3 over the time span 1970–2005.[35] The rapid growth reflects the increase in health care expenditures, the bulk of which is concentrated amongst the over 65-year olds.[36]

7. On the role of medical progress

In the following, we compare the benchmark scenario, in which medical progress against coronary heart disease contributes significantly to the mortality decline from 1980 onwards, against three counterfactual scenarios. The prime counterfactual experiments in Sections 7.1 and 7.2 involve a counterfactual scenario (i), in which we assume medical progress against coronary heart disease to be frozen from 1980 onwards (i.e. the absence of the cardiac revolution); and a counterfactual scenario (ii) in which we assume the full diffusion of medical innovations, implying that all individuals have immediate access to state-of-the art treatments. In the subsequent set of figures, counterfactual (i) is depicted by green, dashed plots, counterfactual (ii) is depicted by red, dotted plots; while the benchmark continues to be depicted by blue, solid plots.

As an extension, we study in Section 7.3 a counterfactual scenario (iii) where innovative health care is subsidized to improve the allocation.

7.1. Counterfactual scenario (i): Absence of medical progress

For this counterfactual scenario, we assume that the state-of-the-art medical technology $M^f(\iota)$ is frozen at the pre-1980 level throughout, implying that we are shutting down the medical progress that marked the cardiac revolution. Comparing this scenario against the benchmark, we obtain insights about the role of medical progress in the treatment of coronary heart disease.

As the left panel of Fig. 7 shows, life expectancy would have increased in the counterfactual scenario (i) from 75.3 in 1980 to 78 in 2005 for reasons unrelated to medical progress against heart disease. The additional contribution of such medical progress

[34] See Frankovic et al. (2020) and Acemoglu and Guerrieri (2008) for analytical representations of the underlying mechanisms.

[35] Notionally, the Medicare tax has been fixed at 2.9% (combining employer and employee contributions) since the mid 1980s. As a fixed tax rate may generate deficits or surpluses to the Medicare budget, we follow the literature (e.g. Zhao, 2014) and consider the finance of Medicare to be part of a general payroll tax. For illustrative purposes, we do, report, however, the implicit Medicare tax.

[36] Between 1980 and 2005 the population share of the 65+ increases from 16% to 18%, while the medical spending share of the population 65+ increases from 34% to 36%.

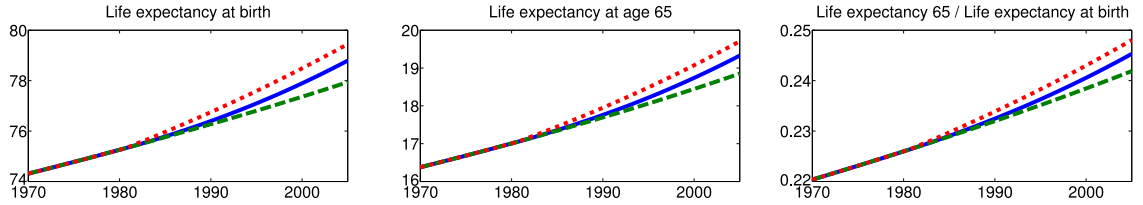

Fig. 7. Life expectancy in the benchmark (blue, solid); absence of medical progress (green, dashed); and perfect diffusion (red, dotted) scenarios.

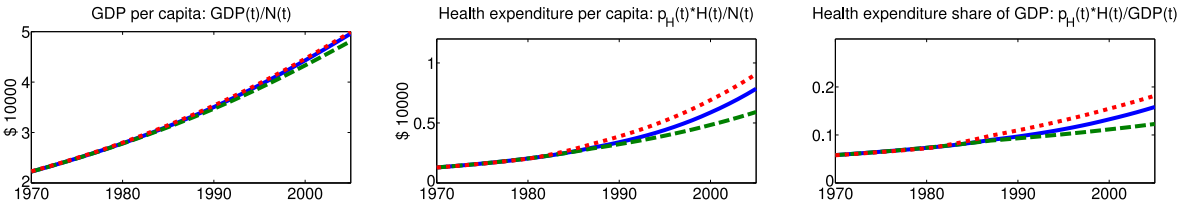

Fig. 8. GDP, health expenditures per capita and GDP share of health expenditure in the benchmark (blue, solid); absence of medical progress (green, dashed); and perfect diffusion (red, dotted) scenarios.

then makes up for another 0.8 years in 2005, implying that around 23% of the total increase in life expectancy are explained by the increasing effectiveness of health care. Given the premise that 32.5% of the increase in life expectancy are related to medical treatments of coronary heart disease, it then follows that 9.5% of the 1980–2005 increase in life expectancy are attributable to increases in health care expenditure (due to income growth and insurance expansion) for a given level of medical effectiveness. The middle and right panel of Fig. 7 illustrate that the increases in life expectancy disproportionately occur towards the later stages of the life-cycle. The ratio between the remaining life expectancy at age 65 and the life expectancy at birth increases over time for all scenarios, reflecting the general mortality decline at advanced ages. We see, however, that this trend is significantly more pronounced in the presence of medical progress, showing the disproportionate propensity for the elderly to benefit from advances in cardiac treatments.

Fig. 8 shows how medical progress bears on health expenditure per capita, the health expenditure share and GDP growth. As the middle panel illustrates, the presence of medical progress leads to a much more pronounced increase in health expenditure per capita. Over the time span 1980–2005, per capita spending grows at an annual rate of 5.6% in the benchmark and at a rate of 4.4% in the absence of medical progress. Hence medical progress during the cardiac revolution has boosted expenditure growth by 1.2 percentage points. Expressed differently, medical progress explains 35% of the 1980–2005 increase in per capita health expenditure.[37] Most of the spending increase can be attributed to the demand expansion that follows an increase in medical effectiveness, a finding that is in line with ample empirical evidence (e.g. Baker et al., 2003; Cutler and Huckman, 2003; Wong et al., 2012; Roham et al., 2014).[38] A comparison between counterfactual (i) and the benchmark then shows that by 2005 medical progress has boosted the health expenditure share by some 3.5 percentage points.

While this amounts to a substantive reallocation of resources, there is little impact of medical progress in the treatment of heart disease on GDP growth. GDP per capita, GDP/N, in 2005 is about 2.4% higher in the presence of medical progress, where a modestly higher GDP per worker G/L by about 2.6% in the presence of medical progress overcompensates a modest decline in the support ratio, L/N, by about 0.2%. The increase in GDP per worker is predominantly due to an increase in the aggregate capital intensity that is afforded by greater wealth accumulation (see below).[39] Over the time span 1980–2005, this amounts to a 0.1 percentage point increase in the annual growth rate of GDP per capita from around 3.2% to 3.3% in the presence of medical progress.

While the impact of medical progress on economic performance is, thus, of a minor magnitude, considerable changes occur in respect to the accumulation of per capita wealth, K/N, and per capita consumption, C/N. Fig. 9 shows that medical progress boosts the accumulation of wealth, with the annual growth rate over the time span 1980–2005 increasing by some 0.36 percentage points from 2.17% to 2.53%. This finding is in line with the expectation that individuals have greater incentives to save if medical progress leads (i) to an increase in life expectancy and thus to a longer spell of retirement for which individuals need to provide;[40] and (ii)

[37] While Fonseca et al. (2020) identify a more modest role for medical progress to explain the increase in US health care spending over the time frame 1965–2005, comparability is difficult due to the different time horizon and the fact that Fonseca et al. (2020) consider a partial rather than general equilibrium setting.

[38] We do not present the plot here, but it can be shown that the impact of medical progress on medical price inflation is small. This finding is well in line with recent evidence that the increase in health care expenditure is predominantly driven by an increase in utilization (Bundorf et al., 2009; Chernew and Newhouse, 2012).

[39] The positive impact of medical progress on GDP per worker, GDP/L, in 2005 can be traced back to a health care share in total employment $1 - L_Y/L$, that is 0.03 percentage points higher and a capital intensity K/L that is 7.1% higher in the presence of medical progress.

[40] Given the fixed retirement age of 65, this increase is equal to the increase in life expectancy at age 65, as depicted in the middle panel of Fig. 7.

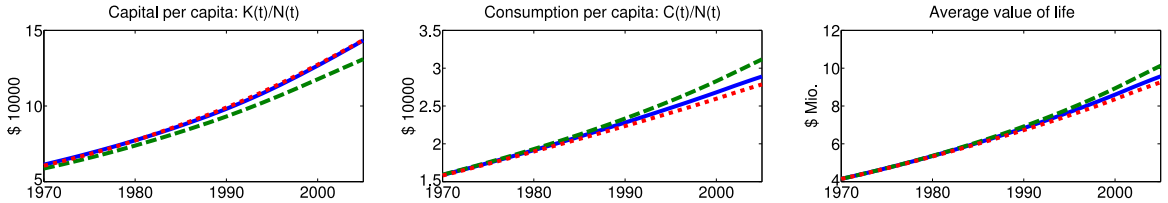

Fig. 9. Per capita values of consumption and capital and the population-weighted average value of life in the benchmark (blue, solid); absence of medical progress (green, dashed); and perfect diffusion (red, dotted) scenarios.

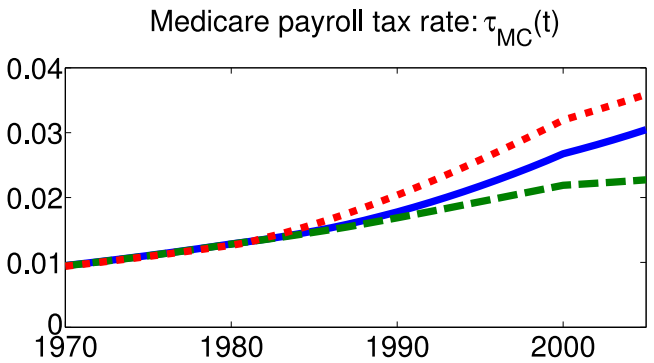

Fig. 10. Medicare tax rate in the benchmark (blue, solid); absence of medical progress (green, dashed); and perfect diffusion (red, dotted) scenarios.

to a greater demand for health care, especially during old age. That the latter is true is reflected in the fact that in our model per capita spending among the over-65-year olds in 2005 in the benchmark scenario is about 1.4 times as high as in the absence of medical progress but only 1.3 times as high for the under-65-year olds. Given that the higher gradient applies to considerably higher spending levels for the over-65-year olds to begin with, the gap is sizeable.[41]

The impact of medical progress on health care expenditure and savings is mirrored by its converse impact on consumption (detail on the individual life-cycle outcomes are contained in Online Appendix A5). As Fig. 9 illustrates, the presence of medical progress lowers the annual rate of per capita consumption growth over the time span 1980–2005 by some 0.3 percentage points from 2% to 1.7%.

While the average value of life grows throughout, surprisingly perhaps, this process is dampened by medical progress. With the value of life being defined by the discounted stream of consumer surplus over the remaining life-cycle [see (22)–(24)], its higher rate of growth in the counterfactual (i) without medical progress reflects the stronger growth of consumption. From the first order condition on the choice of health care, it also follows that the effective price of survival [see (21)] increases at a higher rate in the absence of medical progress. This is intuitive, as more effective health care tends to depress the price of survival (e.g. Cutler et al., 1998; Frankovic et al., 2020).

While the reallocation of income from consumption to health care and savings can be interpreted as an optimal response to medical progress, it is important to recall that the US economy features a number of distortive taxes and subsidies. In particular, the subsidization of health care in the presence of health insurance generates an incentive to consume it at excessive levels. These incentives are particularly pronounced for age groups 65 and above who fall under the comparatively generous coverage of Medicare (see Fig. 2). At the same time, Medicare payments are financed out of the proceeds of a Medicare tax on labor income, implying that health care expenditures on the part of the 65+ impose an intertemporal externality on the working-age population.

Inspection of Fig. 10 reveals that there are good grounds to believe this externality to be of a substantial nature. Notably, it shows that while the Medicare tax would increase even in the absence of medical progress, this increase is much more pronounced in the benchmark in which the cardiac revolution is taken into account. In 2005, the benchmark Medicare tax rate at 3% (implied by a balancing of the Medicare budget) is 30% higher than the rate of 2.3% that would obtain in the absence of medical progress. Expressed differently, medical progress accounts for 41% of the increase in the Medicare tax rate over the time span 1980–2005.

Hence, it is not clear a priori as to whether the medical progress observed over the time span 1980–2005 was improving the welfare of all cohorts alike. In order to address this question, we calculate compensating variations in the spirit of Weil (2014) and Jones and Klenow (2016). Specifically, we calculate the proportion by which we would need to augment the life-cycle consumption of a representative of a given birth cohort living in the counterfactual economy without medical progress, for this representative to

[41] Figure A1 in the Online Appendix A5 shows the impact of medical progress on health care spending over the life-cycle, revealing that the bulk of spending increases occur at higher ages. This is well in line with evidence by Roham et al. (2014) who show that the bulk of the expenditure increase associated with more intensive treatments lies with the age groups 55 and over with a peak increase within the age group 75–79 (see their Figure 6).

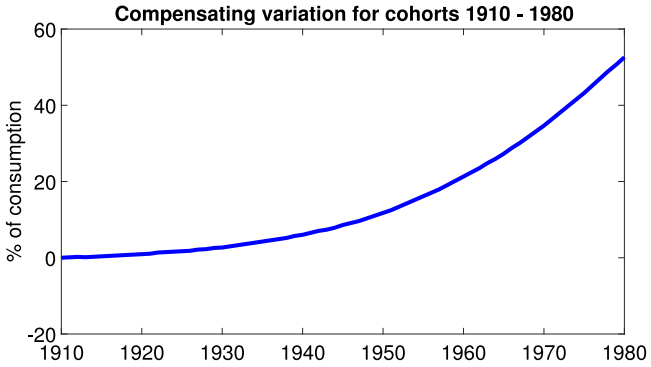

Fig. 11. Compensating variation: no medical progress vs. benchmark.

attain the level of life-cycle utility she would enjoy in the benchmark economy with medical progress. Fig. 11 plots the compensating variation for the birth cohorts 1910–1980. Note that members of the birth cohort 1910 are aged 70 at the onset of the cardiac revolution.[42]

According to our results, medical progress over the course of the cardiac revolution has rendered all cohorts under consideration unambiguously better off. The welfare gains increase monotonously and exponentially with the birth year. This implies that although the costs of better medical technology in terms of foregone consumption as well as the inefficiencies associated with the finance of health care are growing over time, these negative impacts are increasingly overcompensated by the benefit from the cumulative gains to life expectancy brought about by medical progress. In addition, this finding is well in line with earlier results in Hall and Jones (2007) and Kuhn and Prettner (2016), where the value to gains in life expectancy increases disproportionately with income growth. Our findings also illustrate, however, that early-born cohorts received relatively modest gains from the cardiac revolution. Thus, the compensating variation for the 1930 birth cohort, aged 50 at the onset of the cardiac revolution and, thus, prone to considerable medical benefits, amounts to only about 4 percent. Levels of the compensating variation in excess of 10 percent are realized only for cohorts born after the late 1940s.

7.2. Counterfactual scenario (ii): Perfect diffusion

Fig. 4 shows that the imperfect diffusion of new medical innovations leaves a substantial wedge between state-of-the art medicine and the commonly adopted treatments. The implications are explored in counterfactual scenario (ii), in which we assume that frontier medical technology is immediately adopted by all providers such that $M^c(t) = M^f(t)$ holds for all t. The outcomes relating to this counterfactual are graphed as red, dotted plots in Figs. 7 through 10. Perfect diffusion of medical innovations would raise life expectancy over and above the benchmark by an additional 0.6 years to 79.4 in 2005. Put differently, this implies that about 43% of the potential increase in life expectancy by 1.4 years are foregone due to the imperfect diffusion process.

Under perfect diffusion of medical innovations, health expenditure per capita would have grown at a rate of 6.1%, i.e. 0.5 percentage points in excess of the benchmark growth rate. The health expenditure share in 2005 would then stand at 18.3% and, thus, 1.7 percentage points above the benchmark. While in substantive terms this illustrates the drag of imperfect diffusion on both gains to life expectancy and on health expenditure growth, conceptually it also shows that neglecting such imperfections may lead to a misestimation of the role of medical progress. Notably for the perfect diffusion scenario medical progress explains 43% of the 1980–2005 growth in per capita health expenditure an over estimation by about 8 percentage points.

While the reallocation towards health care spending in the presence of perfect diffusion would lead to a further decline in the growth of per capita consumption, this effect is somewhat moderated by the fact that there is only a modest boost to savings. Together this implies that the level of GDP per capita remains largely unaffected. This notwithstanding, perfect diffusion would induce an additional boost to the Medicare tax rate by some 0.5 percentage points bringing it up to 3.5%.

We conclude by calculating the compensating variation between the counterfactual with full diffusion and the benchmark. Fig. 12 plots the percentage change in life-cycle consumption that would afford a representative within the counterfactual economy with full diffusion the (lower) life-cycle utility they would enjoy within the benchmark economy.

As it turns out, representatives of all cohorts would be prepared to give up consumption in exchange for the instantaneous availability of the frontier technology throughout, the compensating variation again increasing in absolute terms with the birth year. While the potential welfare gains from having full diffusion are lower than the welfare gains from having medical progress at all, they are still adding up to about 13% for the 1980 birth cohort. This indicates a sizeable welfare loss arising from limitations in the access to state-of-the-art medicine due to its imperfect diffusion. Notably, this welfare loss is accumulating over time as long as imperfect diffusion leads to a persistent gap between state-of-the-art medicine $M^f(t)$ and "common practice" $M^c(t)$.

[42] We also calculated the equivalent variation, which differs quantitatively only by a small margin.

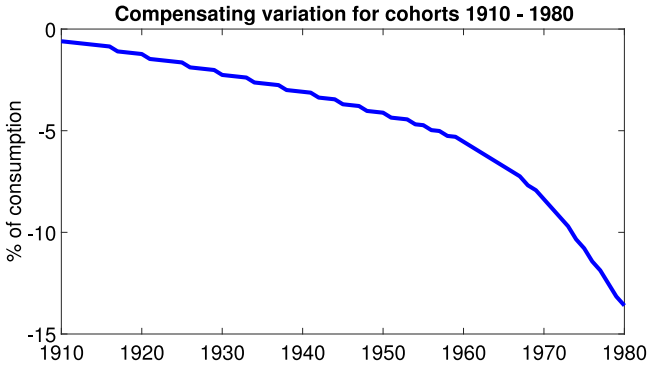

Fig. 12. Compensating variation: perfect diffusion vs. benchmark.

7.3. Counterfactual scenario (iii): Subsidization of innovative health care

In the previous subsection, we have shown that by delaying the access to state-of-the-art medicine, imperfect diffusion leads to sizeable losses in the actual realization of potential improvements in life expectancy, resulting in a non-trivial reduction in welfare for all cohorts. This suggests some scope for policies aimed at the increasing adoption of innovative medicine. While we are unaware of large scale incentive programs to subsidize the adoption of innovative treatments in the US, the 2010 Patient Protection and Affordable Care Act foresees for Medicare and Medicaid the introduction and gradual build up of the Hospital Inpatient Value-Based Purchasing Program (Blumenthal and Jena, 2013). This program is designed as a pay-for-performance program, with an important part of "performance" embracing the adherence to state-of-the-art clinical processes and treatments. Thus, even if not explicitly expressed in this way, the program can be understood to subsidize the adoption of medical innovations (in the broad sense).

Hence, we consider in counterfactual (iii) the extent to which a subsidy on innovative health care can contribute to welfare by promoting a more rapid diffusion of medical innovations. We, thus, assume that innovative health care commands a subsidy at rate $\varphi_f > 0$ on the value of each unit sold, yielding a supply price of $p_H(t)\left(1+\varphi^f\right)$. As shown in Section 3.2, such a subsidy implies a shift in output to innovative providers $F^f(t) > F^c(t)$, yielding them a market share $m(t) > \varrho(t)$ as given by (13). We assume that the total government expenditure on such subsidies

$$p_H(t)\,\varphi^f m(t)H(t) = \tau_{Sub}(t)w(t)L(t)$$

is financed through an ear-marked payroll tax at rate τ_{Sub} tantamount to a top-up on the Medicare tax. A priori, this renders the welfare impact of the subsidy ambivalent. It is easily conceivable that very large subsidies may be required to raise the diffusion of innovative health care to an extent that there is a perceivable impact on survival. The associated tax increase may, thus, lead to a net loss of welfare.

In the following exercise, we consider how different outcomes vary with the rate at which innovative care is subsidized from 1980 onwards. Specifically, we consider the range $\varphi^f \in [0, 0.4]$, with $\varphi^f = 0$ corresponding to our benchmark and $\varphi^f = 0.4$ reflecting a high level of subsidization, which as of to date would not seem to be politically feasible. We should highlight that, in the absence so far of large-scale real-world subsidization of innovative health care, the exercise aims at demonstrating the potential for such subsidies to improve welfare.[43]

Fig. 13 plots for two years, 1990 and 2000, the rate of diffusion, the adoption lag, the market share of innovative providers, and the tax rate τ_{Sub} that is required to finance the subsidy, all as a function of the rate at which innovative care is subsidized. As the figure shows, even subsidies at modest rates below 10% can induce significant improvements to the diffusion process. Thus, a subsidy of innovative care at a rate $\varphi^f = 0.1$ that is implemented in 1980 would raise the rate of diffusion in the year 2000 by 5 percentage points to 15% and thereby halve the adoption lag from 8.9 to around 4.5 years. The lower left panel of Fig. 13 illustrates the increase in the market share of innovative providers $m(t)$ which is underlying the speeding up of diffusion. Recall from (14) that a provider's propensity to adopt the state-of-the-art medicine increases with the density of innovative output mH/N. By inducing a shift in the market share to innovative providers, subsidization is very effective in generating the knowledge spillovers that are underlying a quicker process of diffusion. For a 10% subsidy paid from 1980 onward, the market share of innovative health care in 2000 would almost triple to around 30% as opposed to the benchmark scenario. The lower right panel of Fig. 13 shows that small scale subsidies below 10% can be financed at modest levels of taxation. This changes significantly, however, for larger scale subsidization. Here, tax rates are driven up at any given point in time (i) as the rate of the subsidy itself increases; and (ii) as the market share of innovative health care which is subject to subsidization increases with the rate of the subsidy. These increases are magnified over time, as (iii) the absolute size of the market is growing. As the lower right panel of Fig. 13 illustrates, this leads to a strong growth in taxation over time.

[43] Blumenthal and Jena (2013) report that in pilot programs of value-based prices, the maximum payment premium for high quality/innovative health care was around 2%.

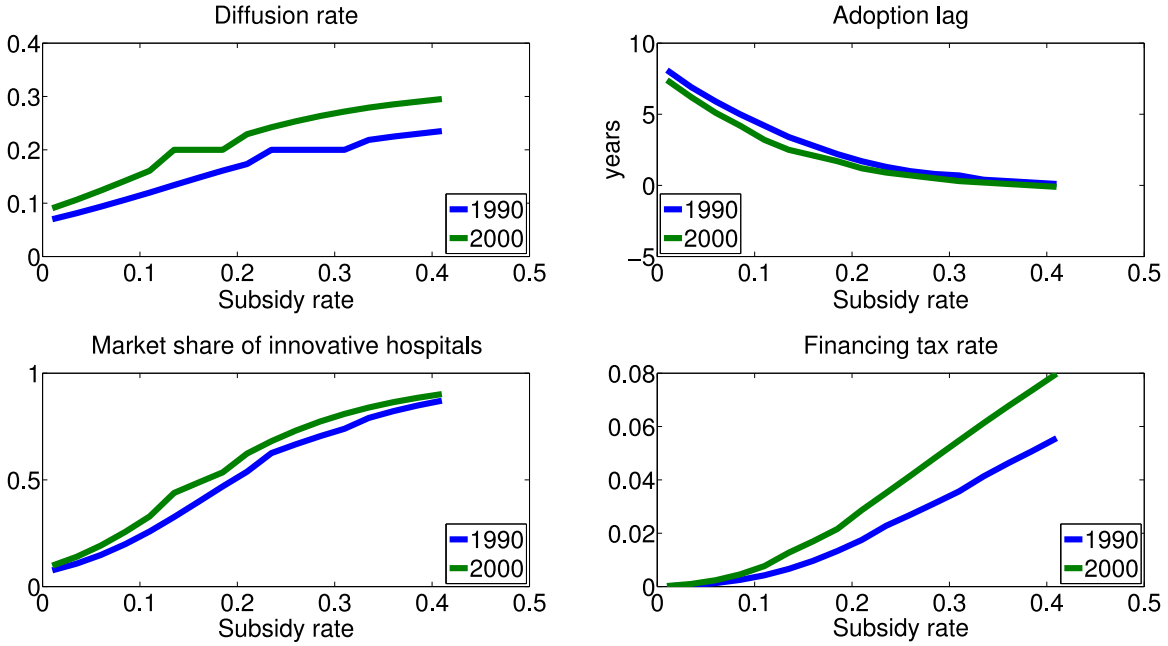

Fig. 13. Rate of diffusion, adoption lag, market share of innovative providers, and financing tax rate for varying rates of subsidization.

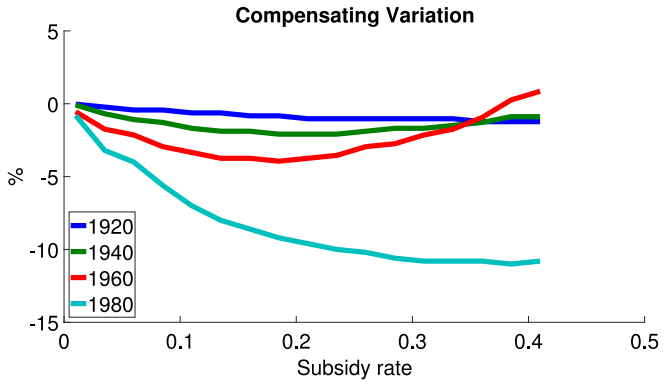

Fig. 14. Compensating variation for varying rates of subsidization.

A priori, it is unclear how the benefits and costs related to the subsidization of innovative health care are distributed across different cohorts. We consider this issue by drawing, again, on a compensating variation exercise. Fig. 14 plots the variation in consumption that renders representatives of a range of birth cohorts indifferent between a counterfactual economy, where innovative health care is subsidized at the rate indicated on the abscissa, and the benchmark economy. In the figure we consider four cohorts born in the years 1920, 1940, 1960 and 1980, respectively.

Unsurprisingly, the early-born 1920 birth cohort tends to benefit less from subsidization than the late-born 1980 cohort: While they face fewer benefits from medical innovation over their remaining life-course, their short remaining working lives at the point of introduction of the subsidies also insulates them from the cost. For similar reasons, the welfare for the 1920 cohort tends to vary little with the rate of subsidy, whereas the 1980 cohort tends to experience large welfare gains from higher subsidization. Strikingly, however, the relationship between the subsidy rate and the compensating variation in consumption turns out to be non-monotonous for the intermediate birth cohorts 1940 and 1960. While these cohorts tend to benefit from increases in the subsidy from low levels, this relationship is reversed for higher levels of subsidization. Notably, the 1960 cohort would even face a welfare loss for rates of subsidization close to the 40% upper limit. The reason for intermediate birth cohorts to benefit less (or even suffer) from subsidization is that these cohorts are exposed to the financial burden of subsidization during their prime working years.

Fig. 15 plots the rate of the subsidy that would maximize the welfare of the birth cohorts born between 1920 and 1980. As it turns out, there is, indeed considerable disagreement across cohorts about the preferred level of subsidization. As the analysis in the previous Fig. 14 has suggested already, the intermediate birth cohorts tend to prefer subsidy rates below 20%, with the 1950

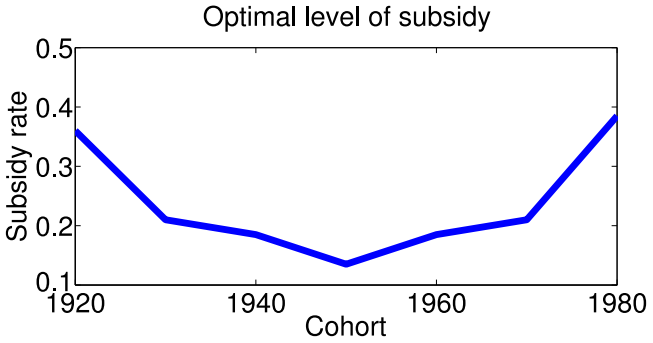

Fig. 15. Preferred subsidization by birth cohort 1910–1980.

cohort preferring the lowest rate of subsidy at around 13.5%. This notwithstanding, the finding also shows that all cohorts would stand to gain from increases in the subsidization of innovative health care to levels up to and beyond 10%. This suggests substantial scope for policy-making to generate welfare gains by fostering the diffusion of innovative medicine.

8. Conclusion

We have set out an OLG model with endogenous survival based on the individual purchase of health care from a medical sector to study (i) whether medical innovations may be detrimental to economic performance or welfare if they lead to a strong expansion of the health care sector at the expense of the rest of the economy; and (ii) the extent to which the slow diffusion of medical innovations is imposing a welfare loss on the economy and to what extent this could be mitigated.

In order to answer these questions we calibrate the model to reflect the development of the US economy and its health care sector over the time span 1980–2005 during which the bulk of medically-related decline in mortality could be ascribed to improvements in the treatment of heart disease. Conveniently, we can employ empirical details about the diffusion process of innovative heart treatments over this time frame. We then contrast the benchmark development against three counterfactual scenarios, involving (i) the absence of medical progress (against heart disease); (ii) the instantaneous diffusion of medical innovations; and (iii) the subsidization of innovative treatments. Our key findings are as follows.

First, we find that the medical innovations that were contributing to the decline in cardiac mortality since the early 1980s could explain 23% of the increase in life expectancy in 2005 with an income-driven expansion of health care expenditure explaining an additional 9.25%. At the same time medical progress against heart disease explains 35% of the increase in health care expenditure per capita. Although medical progress adds 3.5 percentage points to the health care share in 2005, indicating a strong sectoral expansion, there is very little impact of this on GDP growth. In response to medical progress individuals are predominantly reallocating income from consumption away to health care expenditures and, during their working lives, to savings in order to accommodate the purchase of more effective health care in old age. The resulting capital deepening of the economy overcompensates the (modest) decline in the employment rate.

Second, we find that the medical progress against heart disease from the 1980s onwards has brought considerable welfare gains to all cohorts 1910–1980. The presence of a strong welfare gain to medical innovations is well in line with earlier findings (e.g. Jones, 2016; Böhm et al., 2017; Frankovic and Kuhn, 2018; Fonseca et al., 2020). We show, that it is unevenly distributed across cohorts, being significantly larger for later-born cohorts who experience the accumulated gains from medical progress and, at the same time, benefit from additional income growth which raises the willingness to pay for life expansions (Hall and Jones, 2007).

Third, we find that the slow diffusion of state-of-the-art heart treatments that is documented in Skinner and Staiger (2015) leads to a sizeable reduction in the potential gain in life expectancy and in welfare. Although agglomeration effects lead to an increase in the rate of diffusion from a little more than 5% in 1980 to 9.75% in 2005, a time lag of around 9 years remains between the first adoption of a state-of-the art technology and its full diffusion. The treatment of patients with a "common" technology that is persistently lagging behind the state-of-the art is leading to a reduction by 43% in the potential gain in life-expectancy in 2005. Thus, members of the birth cohort 1980 would be willing to give up 13% of their consumption in order to reap the benefit of full diffusion. Again, the welfare loss is smaller for earlier-born cohorts.

Fourth, we find considerable scope for the subsidization of innovative medicine to enhance welfare. By boosting the market share of innovative health care, even relatively modest subsidies at rates up to 10% have the potential to halve the time lag to the full adoption of state-of-the art medicine. For this reason, we find that increases in the subsidization rate to somewhat beyond 10% would constitute an unambiguous Pareto improvement (i.e. raise the welfare of all birth cohorts 1910–1980). Further increases in the rate of subsidization would no longer find unanimous support by all cohorts. This is because middle-born cohorts would find themselves to be exposed to the full burden of the substantial taxation that is required for financing such a program, while at the same time they are not benefiting enough from the accumulation of medical knowledge. This notwithstanding, our results suggests significant scope for programs aimed at the subsidization of innovative medicine, e.g. in the form of pay-for-performance schemes, to improve welfare by speeding up the diffusion of innovative medicine.

We conclude by pointing out a number of limitations to our study. First, the cost of medical innovation, e.g. through the absorption of production factors within a medical R&D sector, may induce a drag on economic growth if these resources are unavailable for R&D into conventional productivity growth (Jones, 2016). Note, however, that within a decentralized economy with R&D-driven growth the increase in the capital intensity of final goods production that follows the absorption of (relatively more) labor by a growing health care sector, provides a stimulus for conventional R&D (Kuhn and Prettner, 2016). The overall effect, thus, remains ambiguous.

Second, the question as to whether additional savings are induced in the wake of a medical innovation depends on the particular design of the social security system (Bloom et al., 2007). Our analysis has been set out against the backdrop of the US health care and social security system, where the limited coverage of old-age insurance generates substantial saving incentives. Some of the European welfare states rely to greater extent on public transfers for the funding of expenditures during old age. Here, the savings response is prone to be weaker, implying that the reduction in the employment rate may not be sufficiently offset by the accumulation of capital.[44]

Third, while our model allows for heterogeneity across age groups and cohorts, we adopt a representative consumer approach within each cohort. For studying the macroeconomic consequences of medical change such an approach is sufficient, given it relies on an accurate representation of the "average" life-cycle of each cohort. In reality, of course, there is large heterogeneity within cohorts. Frankovic and Kuhn (2019) have thus shown within a general equilibrium model that rich and well-educated individuals tend to benefit disproportionately from medical progress. Another interesting dimension of heterogeneity relates to differences in the incidence and severity of illness. With medical progress disproportionately benefiting the ill, one would expect considerable heterogeneity in the welfare assessment of medical innovations, rendering this an interesting extension to our model.

Fourth, we are assuming that medical innovations are of the "product type" rather than the "process type", where the latter would allow the production of services of a given effectiveness at lower cost. While in reality medical innovations can be of either type, and sometimes even of both types in combination, we would suggest that as of now they are, "on balance", reflecting more the product than the process type. This is because process innovations should (a) be characterized by measurable productivity growth, which runs against the evidence by Faere et al. (1997) and Spitalnic et al. (2016), and (b) lead to a decline in the price of health care, which contradicts the observed medical price inflation.[45] Nevertheless, given the important role assigned to cost-effective health care for containing health care expenditure growth and given the ubiquity of cost-ineffective health care (e.g. Chandra and Skinner, 2012) the consideration of both types of innovation constitutes another important extension.

Finally, by modeling diffusion as a reduced-form of knowledge spillovers, we abstract from the fact that the adoption of medical technology is the outcome of deliberate decision making. We present in the Online Appendix B a model with optimal adoption choices on the part of health care providers and argue that, while being numerically intractable, such a model is unlikely to lead to very different quantitative conclusions. We nevertheless, appreciate the scope for future research, focusing more on the microeconomic and institutional detail of health care technology adoption.

CRediT authorship contribution statement

Ivan Frankovic: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing - original draft, Writing - review & editing. **Michael Kuhn:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Supervision, Visualization, Writing - original draft, Writing - review & editing. **Stefan Wrzaczek:** Conceptualization, Funding acquisition, Formal analysis, Methodology, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Supplementary analysis

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jmacro.2020.103262.

[44] Additional offsetting impacts arise if health improvements not only translate into lower mortality but also into a greater propensity to provide labor into older ages (Kuhn and Prettner, 2016).

[45] One could consider an extension to our model where medical innovation comes with both an increase in effectiveness and an increase in productivity. Such a case is compatible with the evidence if the increase in the price of health care due to the expansion of demand dominates the decline in price due to greater productivity. Indeed, the evidence in Cutler and Huckman (2003) shows that the treatment expansion in response to the introduction of innovative angioplasty during the 1980s and 1990s has overcompensated the cost savings associated with the novel treatment. Our set-up amounts to the limiting case where the increase in productivity associated with a new technology is approaching zero.

References

Abeliansky, A.L., Strulik, H., 2018. How we fall apart: Similarities of human aging in 10 European countries. Demography 55, 341–359.
Acemoglu, D., Finkelstein, A., 2008. Input and technology choices in regulated industries: evidence from the US health care sector. J. Polit. Econ. 116, 837–880.
Acemoglu, D., Finkelstein, A., Notowidigdo, M.J., 2013. Income and health spending: evidence from oil price shocks. Rev. Econ. Stat. 95, 1079–1095.
Acemoglu, D., Guerrieri, V., 2008. Capital deepening and nonbalanced economic growth. J. Polit. Econ. 116, 467–498.
Agha, L., Molitor, D., 2018. The local influence of pioneer investigators on technology adoption: evidence from new cancer drugs. Rev. Econ. Stat. 100, 29–44.
Aksoy, Y., Basso, H.S., Smith, R.P., Grasl, T., 2019. Demographic structure and macroeconomic trends. Am. Econ. J.: Macroecon. 11, 193–222.
Baicker, K., Chandra, A., 2010. Understanding agglomerations in health care. In: Glaeser, E.L. (Ed.), Agglomeration Economics. University of Chicago Press, Chicago.
Baker, L., Birnbaum, H., Geppert, J., Mishol, D., Moyneur, E., 2003. The relationship between technology availability and health care spending. In: Health Affairs - Web Exclusive.
Baumol, W.J., 1967. Macroeconomics of unbalanced growth: the anatomy of urban crisis. Amer. Econ. Rev. 57, 415–426.
Bilodeau, D., Cremieux, P.-Y., Jaumard, B., Ouellette, P., Vovor, T., 2004. Measuring hospital performance in the presence of quasi-fixed inputs: an analysis of Quebec hospitals. J. Product. Anal. 21, 183–199.
Bilodeau, D., Cremieux, P.-Y., Ouellette, P., 2000. Hospital cost functions in a non-market health care system. Rev. Econ. Stat. 82, 489–498.
Bloom, D.E., Canning, D., Mansfield, R.K., Moore, M., 2007. Demographic change, social security systems, and savings. J. Monetary Econ. 54, 92–114.
Blumenthal, A., Jena, A.B., 2013. Hospital value-based purchasing. J. Hosp. Med. 8, 271–277.
Böhm, S., Grossmann, V., Strulik, H., 2017. R & D-Driven Medical Progress, Health Care Costs, and the Future of Human Longevity. Mimeo.
Bokhari, F.A.S., 2009. Managed care competition and the adoption of hospital technology: the case of cardiac catheterization. Int. J. Ind. Organ. 27, 223–237.
Bundorf, M.K., Royalty, A., Baker, L.C., 2009. Health care cost growth among the privately insured. Health Aff. 28, 1294–1304.
Carlino, G.A., Chatterjee, S., Hunt, R.M., 2007. Urban density and the rate of invention. J. Urban Econ. 61, 389–419.
Chandra, A., Finkelstein, A., Sacarny, A., Syverson, C., 2016. Health care exceptionalism? Performance and allocation in the US health care sector. Amer. Econ. Rev. 106, 2110–2144.
Chandra, A., Skinner, J., 2012. Technology growth and expenditure growth in health care. J. Econ. Lit. 50, 645–680.
Chandra, A., Staiger, D.O., 2007. Productivity spillovers in health care: Evidence from the treatment of heart attacks. J. Polit. Econ. 115, 103–140.
Chernew, M.E., Newhouse, J.P., 2012. Health care spending growth, chapter 15. In: Pauly, M.V., Barros, P.G. (Eds.), HandBook of Health Economics, Vol. 2. Elsevier.
Chetty, R., 2006. A new method of estimating risk aversion. Amer. Econ. Rev. 96, 1821–1834.
Clark, J.R., Huckman, R.S., 2012. Broadening focus: spillovers, complementarities, and specialization in the hospital industry. Manage. Sci. 58, 708–722.
Comin, D., 2009. On the integration of growth and business cycles. Empirica 36, 165–176.
Comin, D.A., Mestieri, M., 2010. An intensive exploration of technology diffusion. NBER Working Paper 16379.
Comin, D., Mestieri, M., 2014. Technology diffusion: Measurement, causes, and consequences, chapter 2. In: Aghion, P., Durlauf, S.N. (Eds.), HandBook of Economic Growth, Vol. 2B. Elsevier.
Cremieux, P.-Y., Ouellette, P., Rimbaud, F., Vigeant, S., 2005. Hospital cost flexibility in the presence of many outputs: a public–private comparison. Health Care Manag. Sci. 8, 111–120.
Cutler, D.M., 2004. Your Money or your Life: Strong Medicine for America's Health Care System. Oxford UP.
Cutler, D.M., Huckman, R.S., 2003. Technological development and medical productivity: the diffusion of angioplasty in New York State. J. Health Econ. 22, 187–217.
Cutler, D.M., McClellan, M., Newhouse, J.P., Rehmer, D., 1998. Are medical prices declining? Evidence from heart attack treatments. Q. J. Econ. 113, 991–1024.
Dalgaard, C.-J., Strulik, H., 2014. Optimal aging and death: Understanding the preston curve. J. Eur. Econom. Assoc. 12, 672–701.
De Nardi, M., French, E., Jones, J.B., 2010. Why do the elderly save? The role of medical expenses. J. Polit. Econ. 118, 39–75.
Eichner, M.J., 1998. The demand for medical care: what people pay does matter. Amer. Econ. Rev. 88, 117–121, (Papers & Proceedings).
Faere, R., Grosskopf, S., Lindgren, B., Poullier, J.-P., 1997. Productivity growth in health-care delivery. Med. Care 35, 354–366.
Fonseca, R., Michaud, P.-C., Kapteyn, A., Galama, T., 2020. Accounting for the rise of health spending and longevity. J. Eur. Econom. Assoc. (in press).
Ford, E.S., Ajini, U.A., Croft, J.B., Critchley, J.A., Labarth, D.R., Kotte, T.E., Giles, W.H., Capewell, S., 2006. Explaining the decrease in U.S. deaths from coronary disease, 1980–2000. New Engl. J. Med. 356, 2388–2398.
Frankovic, I., Kuhn, M., 2018. Health insurance, endogenous medical progress, and health expenditure growth, TU Vienna Econ Working Paper 01/2018.
Frankovic, I., Kuhn, M., 2019. Access to health care, medical progress and the emergence of the longevity gap: A general equilibrium analysis. J. Econ. Age. 14, 100188.
Frankovic, I., Kuhn, M., Wrzaczek, S., 2020. On the anatomy of medical progress within an overlapping generations economy. Economist 168, 215–257.
Gallet, C.A., Doucouliagos, H., 2017. The impact of health care spending on health outcomes: a meta-regression analysis. Soc. Sci. Med. 179, 9–17.
Gravelle, H., Santos, R., Siciliani, L., 2014. Does a hospital's quality depend on the quality of other hospitals? A spatial econometrics approach. Reg. Sci. Urban Econ. 49, 203–216.
Hall, R.E., Jones, C.I., 2007. The value of life and the rise in health spending. Q. J. Econ. 122, 39–72.
Hansen, G.D., Imrohoroglu, S., 2008. Consumption over the lifecycle: the role of annuities. Rev. Econ. Dyn. 11, 566–583.
Heijdra, B.J., Mierau, J.O., 2012. The individual life-cycle, annuity market imperfections and economic growth. J. Econom. Dynam. Control 36, 876–890.
Huesch, M.D., 2011. Provider-hospital fit and patient outcomes: evidence from Massachusetts cardiac surgeons, 2002–2004. Health Serv. Res. 46, 1–26.
Jones, C.I., 2016. Life and growth. J. Polit. Econ. 124, 539–578.
Jones, C.I., Klenow, P.J., 2016. Beyond GDP? Welfare across countries and time. Amer. Econ. Rev. 106, 2426–2457.
Kelly, M., 2017. Health capital accumulation, health insurance, and aggregate outcomes: A neoclassical approach. J. Macroecon. 52, 1–22.
Kelly, M., 2020. Medicare for all or medicare for none? A macroeconomic analysis of healthcare reform. J. Macroecon. 63, 103170.
Koijen, R.S.J., Philipson, T.J., Uhlig, H., 2016. Financial health economics. Econometrica 84, 195–242.
Kuhn, M., Prettner, K., 2016. Growth and welfare effects of health care in knowledge based economies. J. Health Econ. 46, 100–119.
Kuhn, M., Wrzaczek, S., Prskawetz, A., Feichtinger, G., 2015. Optimal choice of health and retirement in a life-cycle model. J. Econ. Theory 158A, 186–212.
Lee, K.C.L., Sethuraman, K., Young, J., 2015. On the hospital volume and outcome relationship: does specialization matter more than volume. Health Serv. Res. 50, 2019–2036.
Li, J., 2013. Intermediate input sharing in the hospital service industry. Reg. Sci. Urban Econ. 43, 888–902.
Li, J., 2014. The influence of state policy and proximity to medical services on health outcomes. J. Urban Econ. 80, 97–109.
Martin, S., Rice, N., Smith, P.C., 2008. Does health care spending improve health outcomes? Evidence from English programme budgeting data. J. Health Econ. 27, 826–842.
Mierau, J.O., Turnovsky, S.J., 2014. Capital accumulation and the sources of demographic change. J. Popul. Econ. 27, 857–894.
Miller, G., Roehrig, C., Hughes-Cromwick, P., Lake, C., 2008. Quantifying national spending on wellness and prevention. In: Helmchen, L., Kaestner, R., Lo Sasso, A. (Eds.), Beyond Health Insurance: Public Policy to Improve Health. In: Advances in Health Economics and Health Services Research, vol. 19, Emerald Group, pp. 1–24.

Molitor, D., 2018. Evolution of physician practice styles: evidence from cardiologist migration. Am. Econ. J.: Econ. Policy 10, 326–356.
Murphy, K.M., Topel, R.H., 2006. The value of health and longevity. J. Polit. Econ. 114, 871–904.
Nelson, R.R., Phelps, E.S., 1966. Investment in humans, technological diffusion, and economic growth. Amer. Econ. Rev. 56, 69–75.
OECD, 2018. Health Statistics: Causes of Mortality. OECD, Paris, (Accessed 25 June 2018) (OECDi library).
Ouellette, P., Vierstraete, V., 2004. Technological change and efficiency in the presence of quasi-fixed inputs: a DEA application to the hospital sector. European J. Oper. Res. 154, 755–763.
Pauly, M.V., Saxena, A., 2012. Health employment, medical spending, and long-term health reform. CES-Ifo Econ. Stud. 58, 49–72.
Prettner, K., 2013. Population aging and endogenous economic growth. J. Popul. Econ. 26, 811–834.
Reichling, F., Smetters, K., 2015. Optimal annuitization with stochastic mortality and correlated medical costs. Amer. Econ. Rev. 105, 3273–3320.
Rockwood, K., Mitnitski, A., 2007. Frailty in relation to the accumulation of deficits. J. Gerontol.: Med. Sci. 62A, 722–727.
Roham, M., Gabrielyan, A.R., Archer, N.P., Grignon, M.L., Spencer, B.G., 2014. The impact of technological intensity of service provision on physician expenditures: an exploratory investigation. Health Econ. 23, 1224–1241.
Schneider, M.T., Winkler, R., 2016. Growth and welfare under endogenous life-time. University of Bath: Bath Economics Research Papers No. 47/16.
Skinner, J.S., Staiger, D.O., 2015. Technology diffusion and productivity growth in health care. Rev. Econ. Stat. 97, 951–964.
Spitalnic, P., Heffler, S., Dickensheets, B., Knight, M., 2016. Hospital Multifactor Productivity: An Updated Presentation of Two Methodologies. Office of the Actuary, Centers for Medicare & Medicaid Services, U.S. Department of Health and Human Services, https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/ReportsTrustFunds/Downloads/ProductivityMemo2016.pdf.
Suen, R.M.H., 2009. Technological Advance and the Growth in Health Care Spending. Mimeo.
Viscusi, W.K., Aldy, J.E., 2003. The value of a statistical life: A critical review of market estimates throughout the world. J. Risk Uncertain. 27 (1), 5–76.
Warshawsky, M., 1988. Private annuity markets in the United States: 1919–1984. J. Risk Insurance 55, 515–528.
Weil, D.N., 2014. Health and economic growth, chapter 3. In: Aghion, P., Durlauf, S.N. (Eds.), HandBook of Economic Growth, Vol. 2B. Elsevier.
Wong, A., Wouterse, B., Slobbe, L.C.J., Boshuizen, H.C., Polder, J.J., 2012. Medical innovation and age-specific trends in health care utilization: findings and implications. Soc. Sci. Med. 74, 263–272.
Zhao, K., 2014. Social security and the rise in health spending. J. Monetary Econ. 64, 21–37.