Medical innovation, life expectancy, and economic growth

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Abstract

Despite the increasing recognition of the importance of health for economic growth, the role of medical innovation in this process remains largely unexplored. Specifically, what are the causal effects of medical innovation on economic growth, and what shape does this relationship take? To address these questions, we propose an R&D-based economic growth model with overlapping generations, wherein life expectancy depends on healthcare utilization and medical innovation, and we then empirically test the model's implications. Our findings reveal a clear causal pathway from medical innovation to economic growth, with increasing life expectancy serving as a key transmission channel. In the early stages of development, medical innovation does not have a positive effect on economic growth, whereas in intermediate stages, a positive and significant effect emerges. In late stages of development, where life expectancy is already very high, the effect becomes weaker and potentially negative because health improvements are increasingly difficult to achieve and become more resource-intensive.

JEL codes: I15, J11, O41, O47.

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1 Introduction

Average global life expectancy at birth was below the age of 30 prior to the Industrial Revolution. Since then, it has risen continuously to surpass 70 years in 2019. In many rich countries, life expectancy is even higher. Table 1 displays life expectancy in the years 1900 and 2019 for selected countries together with the world average according to the data of Roser (2022). As the last column of the table shows, life expectancy has increased by 60-127% between 1900 and 2019 across the set of countries and aggregates considered.

Table 1: Life expectancy at birth in 1900 versus 2019

Country	Life expectancy (1900)	Life expectancy (2019)	Percentage change
France	45.0	82.7	84%
Germany	45.5	81.3	79%
Italy	41.4	83.5	100%
Japan	38.6	84.6	119%
UK	45.6	81.3	78%
US	49.3	78.9	60%
World average	32.0	72.6	127%

Notes: The data source is Roser (2022). Note that the data for Germany in column 2 are from 1905 and the data for the US are from 1901.

One important driver of these increases is the improvement in living standards that took place from 1900 to 2019. While the positive relationship between income and health — the so-called Preston Curve (Preston, 1975) — is well-established empirically, the causal channels that shape the positive correlation and the potential non-linearities in the effect of life expectancy on economic growth have not been thoroughly investigated.[1]

At least three crucial sets of questions arise. First, although the two-way causality between health and economic growth (or the level of per capita GDP) appears to be widely in line with empirical observations (Bloom and Canning, 2000; Hall and Jones, 2007), there are confounding factors that drive both economic growth and improvements in health. This is most obvious in the case of technological progress, which is the main driver of long-run economic growth (Romer, 1990;

[1]For a non-exhaustive list of contributions to this debate and for different views, see Bhargava et al. (2001), Boucekkine et al. (2002), Shastry and Weil (2003), Acemoglu and Johnson (2007), Weil (2007), Lorentzen et al. (2008), de la Croix and Sommacal (2009), Aghion et al. (2011), Cervellati and Sunde (2011), Bloom et al. (2014), and Bloom et al. (2024).

Jones, 1995; Peretto, 1998) but, at the same time, is a crucial determinant of health (Acemoglu and Johnson, 2007).

Second, the effect of health on economic growth depends heavily on the economic, demographic and medical state of development (see also Cervellati and Sunde, 2011). In this context, the theory of the epidemiological transition as described by Omran (1998) provides a suitable framework for characterizing the dependence of economic growth on health improvements. Omran (1998) proposes distinguishing between five stages of the epidemiological transition, during which medical advances have different effects on different parts of the population. While the 1^{st} stage ("pestilence and famine"), a Malthusian stage without much of a role for medicine, and the 5^{th} stage ("aspired quality of life with persistent inequalities"), a futuristic stage of the epidemiological transition, lie outside the time frame of our analysis, the 2^{nd} to 4^{th} stages are highly relevant for our theoretical and empirical analyses. In the 2^{nd} stage ("receding pandemics"), health improvements mainly affect child mortality but not yet adult mortality and workforce growth. In this stage, mainly the young cohorts grow resulting in an "inverse demographic dividend" (Bloom et al., 2003) involving a temporary increase in the dependency ratio. In the 3^{rd} stage ("degenerative, stress, and man made diseases"), medical improvements reduce adult mortality, leading to positive impacts on workforce growth and fostering investment. During this stage, medical innovations are likely to have positive effects on economic growth, not least because improvements in health are not yet highly resource intensive. For example, advancements in the treatment of cardiovascular diseases have resulted in significant improvements in life expectancy at relatively low treatment costs.[2] Finally, in the 4^{th} stage ("declining cardiovascular mortality, ageing and emerging diseases"), improvements in health mainly pertain to older adults who have already surpassed the working age. In addition, the health improvements from medical interventions for the entire population tend to be more limited and require increasingly more resources in terms of healthcare personnel (a phenomenon known as flat-of-the-curve medicine; see Fuchs, 2004). These workers are no longer available for other sectors, such as industrial research and development (R&D), which can hinder economic growth. All of this indicates that improvements in health will lead to faster economic growth during the 3^{rd} stage of the epidemiological transition but may have a more ambiguous impact during the 2^{nd} and 4^{th} stages.

Third, little is known about how medical innovation combines with industrial innovation as a driver in the nexus of longevity and income growth. When medical and industrial R&D efforts compete for the same resources, medical and industrial innovation can be seen as substitutes (Jones, 2016; Kuhn and Prettner, 2016). However, this ignores the role of spillovers across R&D

[2]Here, the 3^{rd} and 4^{th} stages are blending into each other; while early advances against cardiac disease have benefited the (late) working-age population, later advances were mostly benefiting retirees and would be considered part of the 4^{th} stage as defined by Omran (1998).

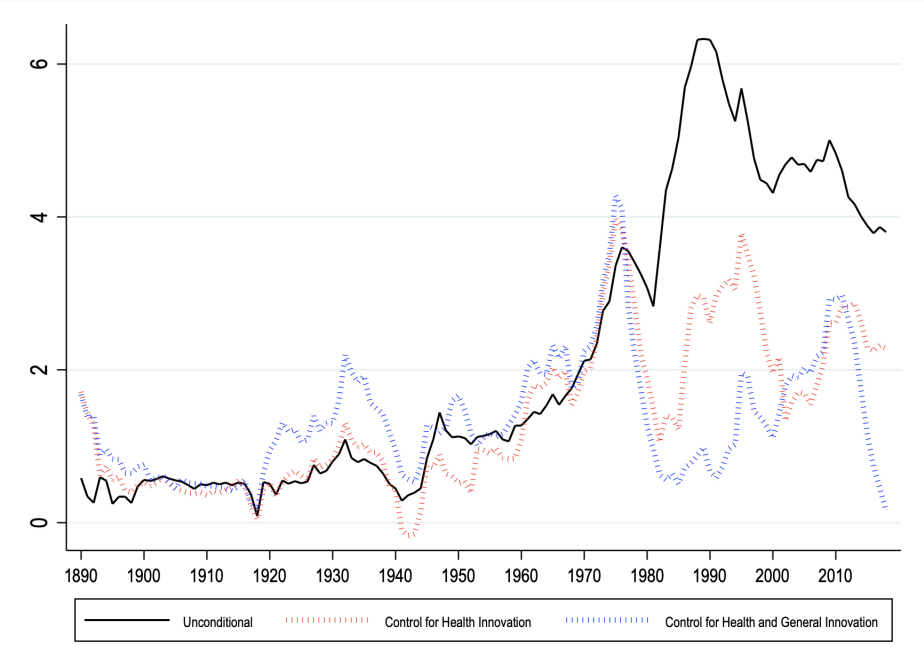
projects, where advances in industrial R&D (e.g., imaging and radiation, laser, robotic technologies) are often the basis for medical innovations, and vice versa. Moreover, it is well known that by raising the demand for health care, income growth itself acts as a driver of medical innovation (Hall and Jones, 2007; Jones, 2016; Frankovic and Kuhn, 2023; Kuhn, 2023), while, in the long run, the health improvements resulting from medical innovation facilitate industrial innovation by creating a healthier and more educated workforce.

Against this backdrop, Figure 1 illustrates, for the time frame 1890-2020, the annual co-movement between GDP per capita and life expectancy at birth for the sample of industrialized countries considered in this study (see below for details).[3] The solid line is the bi-variate (unconditional) correlation, the dashed red line refers to the correlation obtained when controlling for the impact of medical innovation on income per capita, whilst the dashed blue line is the correlation arising when accounting for the effects of both medical and industrial innovation. The figure shows that the co-movement between longevity and GDP per capita was relatively low for the first half of the period, but it increased sharply after WWII, reaching a peak in the late 1980s. Since then, the correlation has decreased by one third. The parameters of longevity obtained from conditional regressions followed a similar pattern until the mid-1970s but remained relatively low thereafter. In brief, the graph suggests that the longevity-income link is non-linear and that since the 1970s, a significant portion of the co-variation has been explained by both medical and industrial innovation. This corroborates the narrative described above.

We aim to shed additional light on the role of medical innovation as a driver of longevity and income growth *i*) by proposing a theoretical model of knowledge-driven growth that includes health and health interventions driven by medical innovation and takes account of the non-linearities in this context; *ii*) by explicitly distinguishing industrial and medical innovation in a panel time series regression analysis, thereby isolating the effect of medical innovation on economic growth. In so doing, we are the first to utilize a rich dataset that enables us to distinguish patents that underlie industrial innovation from patents that are specific to medical innovation. We identify the income effect of medical innovation through an event analysis that compares the change in GDP per capita observed after the launch of these innovations with that of countries that did not introduce them. We validate the results of this analysis by using alternative identifying assumptions and expanding the regression to a global sample of countries to address the econometric issues associated with this type of estimation. We also estimate the linkage between medical innovation, longevity and income levels through cointegration methods of regressions.

[3]Figure 1 reports the year-to-year elasticity obtained regressing GDP per capita against life expectancy (both expressed in logs) using the panel Mean-Observation OLS regression (Keane and Neal, 2020). Because of endogeneity issues, we label the estimated coefficients as correlation parameters even if their range of variation may go outside the unit circle.

Figure 1: Year-by-year co-movement between longevity and GDP per capita



Notes: The graph reports the yearly parameter estimates, $\bar{\beta}_t$, obtained from a MO-OLS regression of GDP per capita against life expectancy, controlling for medical innovation and industrial innovation (both expressed as patent stock per inhabitant): $\ln GDPpc_{it} = \alpha_i + \beta_{it} \ln X_{it} + \epsilon_{it}$ with $\bar{\beta}_t = \sum_{i=1}^{N} \beta_{it}$.

Among other factors, we control for various measurement issues and employ alternative model specifications. Reassuringly, the impact of medical innovation estimated using this technique is extremely close to the income increase obtained from the event analysis. Note that our main dataset begins in 1890 and therefore spans more than a century. This implies that we can distinguish between periods in which health improvements i) mainly reduce infant mortality and lead to fast population growth of young cohorts during the early stage of development as defined by the epidemiological transition; ii) mainly affect the working-age population in the intermediate stage of development; and iii) come with increasing resource requirements and mainly benefit older adults potentially beyond their working age in late stages of development. This, in turn, allows us to analyze potential stage dependencies to the extent to which economic growth reacts to improvements in health and medical innovation. Overall, our analysis contributes to the literature a distinctly innovation-based and, in terms of unpacking different channels over time, a more nuanced view on the nexus between health and economic growth.

The paper is organized as follows. In Section 2, we propose a theoretical model to describe the effects of medical innovation and life expectancy on economic growth when growth is driven by purposeful R&D investments. In Section 3, we present the empirical specifications that underpin our econometric work, while Section 4 contains the description of the data. Section 5 is devoted

to the presentation of the empirical findings. Finally, in Section 6, we conclude and draw lessons for policymakers.

2 Model

2.1 The demographic structure

Households consist of overlapping generations in the spirit of Blanchard (1985). Specifically, the total population is composed of different cohorts that are identified by their date of birth t_0. Each cohort consists of a measure $N(t_0, t)$ of individuals at a certain point in time $t > t_0$. Individuals face a constant risk of death at each instant, which we denote by $\mu(t)$. Due to the law of large numbers, this rate is equal to the fraction of the population dying at each instant. The population grows at rate $n(t) \equiv \beta(t) - \mu(t)$, with $\beta(t)$ referring to the birth rate, which is equal to the period fertility rate in this demographic structure. It follows that, at time t, the size of a cohort born at $t_0 < t$ amounts to $N(t_0, t) = \beta N(0) e^{\beta t_0} e^{-\mu t}$, where $N(0)$ refers to the initial population size. Using the demographic assumptions, we show in Appendix A.1 that the population size at time t amounts to

$$N(t) = \int_{-\infty}^{t} N(v, t) \mathrm{d}v = N(0) e^{nt}.$$

When the birth rate $\beta(t)$ is equal to the death rate $\mu(t)$, we have $n = 0$ and the population stays constant.

2.2 Healthcare

In the healthcare sector, a representative firm provides medical treatment by employing labor. Following Kuhn and Prettner (2016), we assume that one unit of labor produces one unit of medical treatment such that

$$h(t) N(t) = L_H(t),$$

where $L_H(t)$ is aggregate employment in the healthcare sector and $h(t)$ is healthcare per capita. Consumption of healthcare per capita, $h(t) = L_H(t)/N(t)$, is therefore proportional to per capita employment in the healthcare sector.

2.3 Mortality and fertility

As in Hall and Jones (2007) and Schneider and Winkler (2021), among others, we assume that the consumption of a quantity $h(t)$ of healthcare lowers mortality.[4] Moreover, following Frankovic et al. (2020) and Frankovic and Kuhn (2023), medical technology $M(t)$ contributes to reducing mortality with (weakly) decreasing returns, that is $\mu_M < 0$ and $\mu_{MM} \geq 0$, where the subscript denotes the derivative with respect to the corresponding variable. Expressing the mortality rate as $\mu(h(t), M(t))$, we then get

$$\frac{d\mu(h(t), M(t))}{dM(t)} = \mu_M + \mu_h \frac{dh(t)}{dM(t)}.$$

Medical innovation, $M(t)$, has therefore a twofold impact on the mortality rate. Firstly, it directly allows people to live longer. Secondly, it triggers healthcare spending which, in turn, curbs mortality. Thus, following well-established evidence that medical innovations typically lead to an increase in healthcare utilization,[5] we assume that the state of medical technology increases the consumption of healthcare, i.e., $dh(t)/dM(t) > 0$, which implies $d\mu(t)/dM(t) < 0$.

Medical innovation, as measured by the increasing stock of $M(t)$, has also the potential to curb child and early life mortality. Interpreting the fertility rate as a measure of surviving children (net fertility)[6] implies that $\beta(M(t))$ is a positive function of $M(t)$, that is,

$$\frac{\partial \beta(M(t))}{\partial M(t)} = \beta_M > 0.$$

Considering all these effects, medical innovation has an unambiguously positive impact on population growth, $n(t)$, such that $\partial n(t)/\partial M(t) = \partial \beta(t)/\partial M(t) - \partial \mu(t)/\partial M(t) > 0$.[7]

2.4 Consumption

An individual belonging to the cohort born at t_0 maximizes her discounted stream of lifetime utility

$$U = \int_{t_0}^{\infty} e^{-(\rho+\mu)(s-t_0)} \log c(t_0, t) \mathrm{d}s, \tag{1}$$

[4] Crémieux et al. (1999), Cutler et al. (2006), Hall and Jones (2007), and Baltagi et al. (2012) provide empirical evidence on the impact of healthcare on mortality.

[5] See, for example, Baker et al. (2003), Cutler and Huckman (2003), Wong et al. (2012), and Roham et al. (2014).

[6] In the seminal paper on endogenous fertility by Barro and Becker (1989), falling infant mortality rates lower the cost of having a surviving child and, therefore, net fertility increases as mortality declines. Doepke (2005) examines three variants of the Barro-Becker model to allow for different plausible assumptions with respect to preferences/uncertainty and shows that the number of surviving children increases in all three extensions as child mortality declines.

[7] Herzer et al. (2012) show that, over the last century, the fertility reduction triggered by declining mortality was not enough to overcompensate for the positive effect of falling mortality on population growth.

where $c(t_0, t)$ refers to individual consumption of the final good. The subjective time discount rate $\rho > 0$ is augmented by the mortality rate $\mu(t) > 0$ because individuals who face the risk of death are more reluctant to postpone consumption into the future.

At any time individuals are alive, they are endowed with one unit of labor, which they supply inelastically on the labor market at the wage rate $w(t)$. Following Yaari (1965), we assume the presence of a perfect annuity market in which individuals insure themselves against the risk of dying with positive assets. Thus, individuals do not receive and do not leave bequests. They spend their available income on healthcare $h(t)$ and consumption $c(t)$, the price of which is normalized to one. Individual assets $a(t)$ yield an annuity premium $\mu(t)$ in addition to the interest rate $r(t)$ and therefore evolve according to

$$\dot{a}(t) = [r(t) + \mu]a(t) + w(t) - m(h, t) - c(t),$$

where $m(h, t)$ denotes the cost of healthcare. Inserting $m(h, t) = h(t)w(t)$ into the household budget constraint yields

$$\dot{a}(t) = [r(t) + \mu]a(t) + w(t)[1 - h(t)] - c(t), \tag{2}$$

which shows that the level of medical treatment, $h(t)$, can be interpreted as the fraction of labor income that an individual spends on healthcare services. In Appendix A.2, we show that utility maximization subject to the wealth constraint yields the standard Euler equation

$$\frac{\dot{c}(t)}{c(t)} = r(t) - \rho,$$

stating that optimal individual consumption expenditures grow as long as the interest rate exceeds the subjective time discount rate.

2.5 Aggregation

Agents are heterogeneous with respect to age. To get expressions of the dynamic behavior of aggregate assets, $\Omega(t)$, and aggregate consumption, $C(t)$, we apply the following rules to integrate over all cohorts alive at time t (cf. Heijdra, 2017)

$$\Omega(t) \equiv \int_{-\infty}^{t} a(t_0, t)N(t_0, t)\mathrm{d}t_0 = e^{-\mu t}\beta N(0) \int_{-\infty}^{t} a(t_0, t)e^{\beta t_0}\mathrm{d}t_0,$$

$$C(t) \equiv \int_{-\infty}^{t} c(t_0, t)N(t_0, t)\mathrm{d}t_0 = e^{-\mu t}\beta N(0) \int_{-\infty}^{t} c(t_0, t)e^{\beta t_0}\mathrm{d}t_0.$$

From the two previous equations, we obtain the following expressions for the aggregate Euler equation and the law of motion of aggregate assets (see Appendix A.3)

$$\frac{\dot{C}(t)}{C(t)} = r(t) - \rho + n(t) - [n(t) + \mu(t)]\,[\rho + \mu(t)]\,\frac{\Omega(t)}{C(t)}, \tag{3}$$

$$\dot{\Omega}(t) = r(t)\Omega(t) + w(t)[1 - h(t)]N(t) - C(t). \tag{4}$$

Eq. (3) shows that the aggregate Euler equation differs from the individual Euler equation. The reason for this is that older people have higher income and consumption levels such that the ongoing process of generational replacement (older people die and are replaced by newborns) reduces aggregate consumption growth as compared with individual consumption growth (see, e.g., Prettner, 2013; Kuhn and Prettner, 2016, 2018 for details).

2.6 Production

Final output, $Y(t)$, which can be either consumed by individuals in the economy or invested in the production of intermediates, is produced according to the function

$$Y(t) = L_Y(t)^{1-\alpha} \int_0^{A(t)} x_i(t)^{\alpha} di,$$

where $L_Y(t)$ refers to labor employed in final goods production, $x_i(t)$ to the amount of intermediate i used in final goods production, $A(t)$ to the stock of technologies as determined by the industrial innovation sector, and α to the elasticity of output with respect to the input of intermediate i. Assuming perfect competition in this sector, the factor rewards amount to

$$w_Y(t) = (1-\alpha)\frac{Y(t)}{L_Y(t)},$$
$$p_i(t) = \alpha L_Y(t)^{1-\alpha} x_i(t)^{\alpha-1}.$$

Next, we assume that intermediate goods are produced with physical capital utilizing a linear technology with a unitary capital input coefficient such that $x_i(t) = k_i(t)$, where $k_i(t)$ is the capital employed by one intermediate goods producer i. Using all the ingredients we have so far and denoting the price of an intermediate variety i by $p_i(t)$, we get profits in the intermediate goods sector as

$$\pi_i(t) = p_i(t)k_i(t) - r(t)k_i(t) = \alpha L_Y(t)^{1-\alpha} k_i(t)^{\alpha} - r(t)k_i(t).$$

Profit maximization implies the optimal mark-up pricing strategy

$$p_i(t) = \frac{r(t)}{\alpha},$$

which shows that symmetry prevails such that the index i can be dropped. We use this result to rewrite the interest rate as (see Appendix A.4)

$$r(t) = \alpha p(t) = \alpha^2 L_Y(t)^{1-\alpha} x(t)^{\alpha-1} = \alpha^2 \frac{Y(t)}{K(t)},$$

where $K(t) = A(t)x(t)$ is the aggregate capital stock. With this information, we can rewrite final output as (see Appendix A.5)

$$Y(t) = [A(t)L_Y(t)]^{1-\alpha}K(t)^{\alpha}.$$

Overall, the value of all assets in the economy is

$$\Omega(t) = K(t) + A(t)V_A(t),$$

where the stock of technologies, $A(t)$, coincides with the number of intermediate goods producers because each of these companies must make a fixed up-front investment by purchasing a patent before it can begin production. As the fixed production costs are equal to the total discounted stream of the firm's operating profits (a new entrant would always be willing to bid at a lower price), $V_A(t)$ represents the value of both the intermediate goods producer and the individual patent.

The gross domestic product (GDP) of the economy is then defined as

$$GDP(t) = Y(t) + P_H(t)H(t) + V_A(t)\dot{A}(t),$$

where $P_H(t) = w(t)$ is the price of healthcare, $H(t)$ is the output of the healthcare sector, and $V_A(t)\dot{A}(t)$ is the value created by the R&D sector.

2.7 R&D sector

The production function for new industrial technologies is given by

$$\dot{A}(t) = \nu(\bar{\tau})A(t)\left[\frac{L_A(t)}{N(t)}\right],$$

where $\nu(\bar{\tau})$ is the productivity of researchers, which, according to the estimates of Jones (2010) and Jones and Weinberg (2011), depends on the average age of the population denoted by $\bar{\tau}$, $L_A(t)/N(t)$ is the share of researchers in the population, and $A(t)$ on the right-hand side of the equation captures intertemporal knowledge spillovers. This formulation sterilizes the strong scale effect of population size on economic growth (Jones 1995).[8] Below, we assume that the productivity of researchers follows a hump-shaped pattern in relation to their average age, that is $\nu_{\bar{\tau}} > 0$ and $\nu_{\bar{\tau}\bar{\tau}} < 0$. This assumption is based on the observation that researchers tend to

[8] Models of endogenous growth, in which an increase in the growth rate of the stock of researchers (due to population growth) generates faster steady-state output growth, are inconsistent with the data. In order to avoid such bias and ensure a balanced growth path, we divide the number of researchers by the total population (see Laincz and Peretto 2006; Peretto 1998).

display different levels of productivity throughout their careers, with an initial increase, followed by a peak, and eventually a decline as they age. This pattern has been described and estimated by Feyrer (2008), Jones (2010), Jones and Weinberg (2011), and Jones et al. (2014). These studies, which analyze the age profile of inventors and innovators, suggest that the frequency of inventions by middle-aged individuals is significantly higher than that observed for younger and older individuals, with the peak productivity years typically falling between the mid-30s and early 40s.

There are two saving vehicles, namely physical capital, which pays an interest rate $r(t)$, and shares of firms, which pay dividends and yield a valuation gain when sold. The no-arbitrage equation for these two investments implies that both saving vehicles need to pay the same rate of return such that

$$r(t) = \frac{\pi_A(t)}{V_A(t)} + \frac{\dot{V}_A(t)}{V_A(t)}.$$

After reformulating and acknowledging that $\pi_A(t) = \alpha(1-\alpha)Y(t)/A(t)$, we get

$$V_A(t) = \frac{\alpha(1-\alpha)Y(t)/A(t)}{r(t) - \dot{V}_A(t)/V_A(t)}.$$

Due to free entry in the R&D sector, the revenue of an R&D firm (which is the total value of the patent multiplied by the new patents produced) must equal the wage bill of the firm. This means that

$$V_A(t)\dot{A}(t) = w(t)L_A(t).$$

Perfect labor mobility leads to equalization of wages across sectors. Therefore, by inserting the expression for wages $w(t) = (1-\alpha)Y(t)/L_Y(t)$ into the previous equation, we obtain

$$\frac{L_Y(t)}{N(t)} = \frac{r(t) - \dot{V}_A(t)/V_A(t)}{\alpha\nu(\bar{\tau})},$$

which represents the share of labor employed in the final goods sector.

2.8 Market clearing and steady-state growth

Along a balanced growth path, we have $\dot{A}(t)/A(t) = g(t)$, $\dot{V}_A(t)/V_A(t) = n(t)$, and hence aggregate output grows at the rate of population growth plus the rate of technological progress, $\dot{Y}(t)/Y(t) = n(t) + g(t)$. With this information, we can rewrite

$$\frac{L_Y(t)}{N(t)} = \frac{r(t) - n(t)}{\alpha\nu(\bar{\tau})}, \qquad \frac{L_A(t)}{N(t)} = \frac{g(t)}{\nu(\bar{\tau})}.$$

Assuming that labor markets clear, *i.e.*, $L_H(t) + L_A(t) + L_Y(t) = N(t)$, and using the previous results, we get the growth rate of the technological frontier, namely

$$g(t) = \frac{\dot{A(t)}}{A(t)} = \nu\frac{L_A(t)}{N(t)} = [1 - h(t)]\nu(\bar{\tau}) - \frac{r(t) - n(t)}{\alpha}. \tag{5}$$

Since $\dot{C}(t)/C(t) = \dot{\Omega}(t)/\Omega(t) = n(t) + g(t)$ along a balanced growth path, Eqs. (3) and (4) can be written, respectively, as

$$g(t) = r(t) - \rho - [n(t) + \mu(t)][\rho + \mu(t)]\frac{\Omega(t)}{C(t)}, \tag{6}$$

$$g(t) = r(t) - n(t) + [1 - h(t)]w(t)\frac{N(t)}{\Omega(t)} - \frac{C(t)}{\Omega(t)} = r(t) - n(t) + [1 - h(t)]\frac{r(t)\nu(\bar{\tau})(1-\alpha)}{r(t) - \alpha n(t)} - \frac{C(t)}{\Omega(t)}, \tag{7}$$

where the last equality of (7) follows from the fact that $w(t)N(t)/\Omega(t) = r(t)\nu(\bar{\tau})(1-\alpha)/[r(t) - \alpha n(t)]$ (see Appendix A.6 for the derivation). Therefore, our economy is described by the dynamic system composed of Eqs. (5)-(7). These equations determine the interest rate, $r(t)$, the ratio of consumption to assets, $C(t)/\Omega(t)$, and the economic growth rate, $g(t)$. Below, we drop time indices, whenever this does not impair the clarity of the exposition.

In Figure 2, we provide a graphical representation of the balanced growth allocation in $(C/\Omega, r)$ space (left panel) and (g, r) space (right panel). As shown in Appendices A.7 and A.8, setting Eq. (5) equal to Eq. (6), implying balanced growth of technology and consumption, yields a downward-sloping locus relating r to C/Ω (the r_d locus); whereas setting Eq. (5) equal to Eq. (7), implying balanced growth of technology and assets, results in an upward-sloping locus in the same space (the r_u locus). The balanced-growth equilibrium is determined by the intersection of the two loci at point E_1. It can be ascertained that the r_d locus shifts up if either research productivity, ν, the mortality rate, μ, or the population growth rate, n, increases, and shifts down if the per capita level of medical treatment, h, increases. Furthermore, the r_u locus shifts up if research productivity, ν, or the population growth rate, n, increases and shifts down if the per capita level of healthcare, h, increases. The inverse relationship between r and g provided by Eq. (5) is depicted in the right panel of Figure 2 (the r_g locus). An increase in either research productivity, ν, or the population growth rate, n, induces a parallel upward shift of the r_g locus, whereas an increase in the per capita level of medical treatment, h, results in a parallel downward shift of this locus.

2.9 The channels through which medical progress affects economic growth

As described above, our model relates to the theory of the epidemiological transition developed by Omran (1998) on the channels through which medical technology impacts economic growth. According to this theory, societies experience five stages in the path to epidemiological modernization.[9] For our purpose, only the 2^{nd} to 4^{th} stages are relevant. During the 2^{nd} stage ("receding

[9]In his original work, Omran (1971) was only referring to three stages, but in the light of the rapid medical and epidemiological developments during the 1970s and 1980s, he revised this to five stages for Western indus-

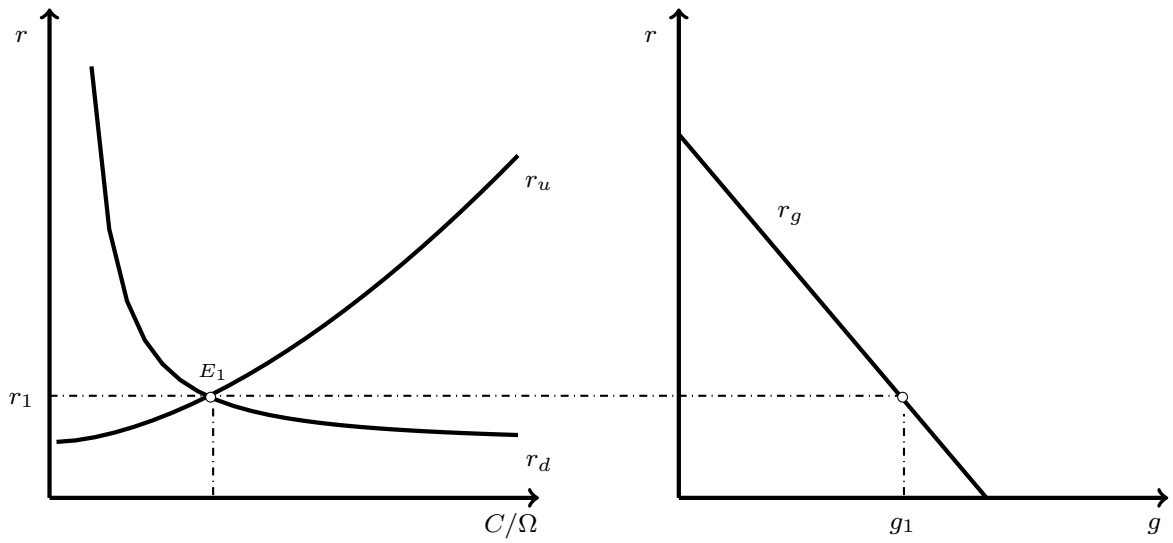


Figure 2: Balanced growth equilibrium.

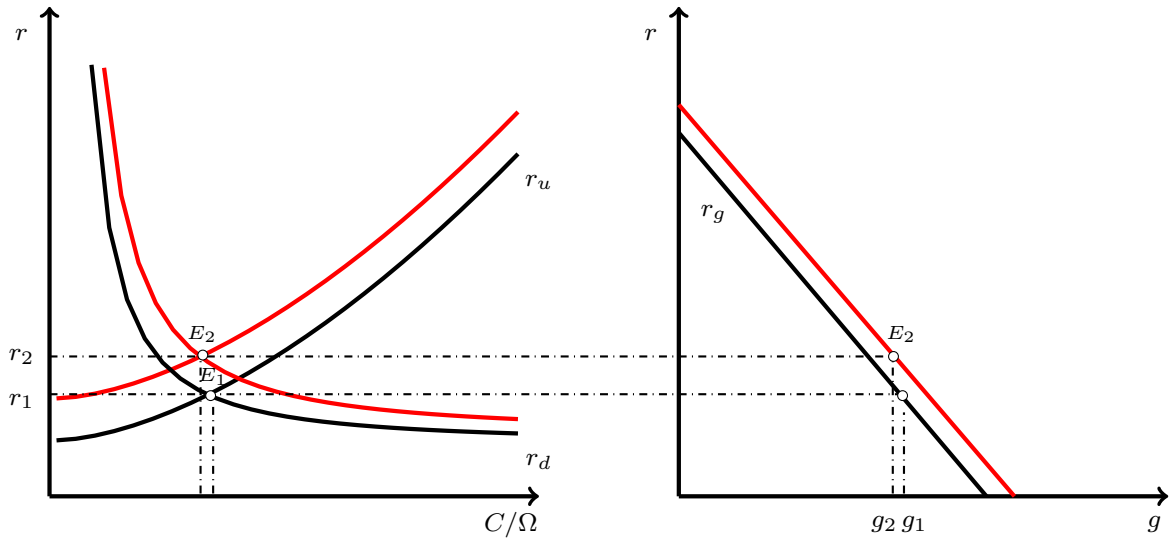
pandemics"), the prevalence of pandemics and famines decreases, and life expectancy increases to about 50 years. During the $3rd$ stage ("degenerative and man-made diseases"), the rate of mortality decrease slows down, while heart diseases, strokes, diabetes and deaths caused by pollution become increasingly frequent. During this stage, life expectancy increases to about 75 years. In the 4^{th} stage ("declining cardiovascular mortality, ageing and emerging diseases"), progress against cardiovascular mortality increases life expectancy to about 80 to 85 years, while the rise of chronic diseases and aging result in high medical costs for both governments and individuals. Below, we analyze the effect of medical innovation during the 2^{nd} to 4^{th} stages of the epidemiological transition that are covered by our available data. For the sake of simplicity, we also refer to these stages as early, intermediate, and late development stages.

The 2^{nd} and early 3^{rd} stages of the epidemiological transition

During the 2^{nd} stage of the epidemiological transition, medical innovation leads to a reduction in child and early life mortality, implying that $\partial n/\partial M > 0$ and $\partial \mu/\partial M$ is small and close to 0. Moreover, since there is no role for the healthcare utilization channel, we assume that $\partial h/\partial M = 0$. Medical innovation therefore raises the rate of population growth, n, and both the r_d and r_u loci shift up (see Figure 3). It then follows that the impact of medical progress on the interest rate, r, is positive (whereas that on the ratio C/Ω is ambiguous). The r_g locus shifts up when n increases, with an ambiguous impact on the rate of economic growth. As can be seen, two equilibria are possible: E_2 in the top panel and E_3 in the bottom panel of Figure 3. If the r_g

trialized countries.

Top panel



Bottom panel

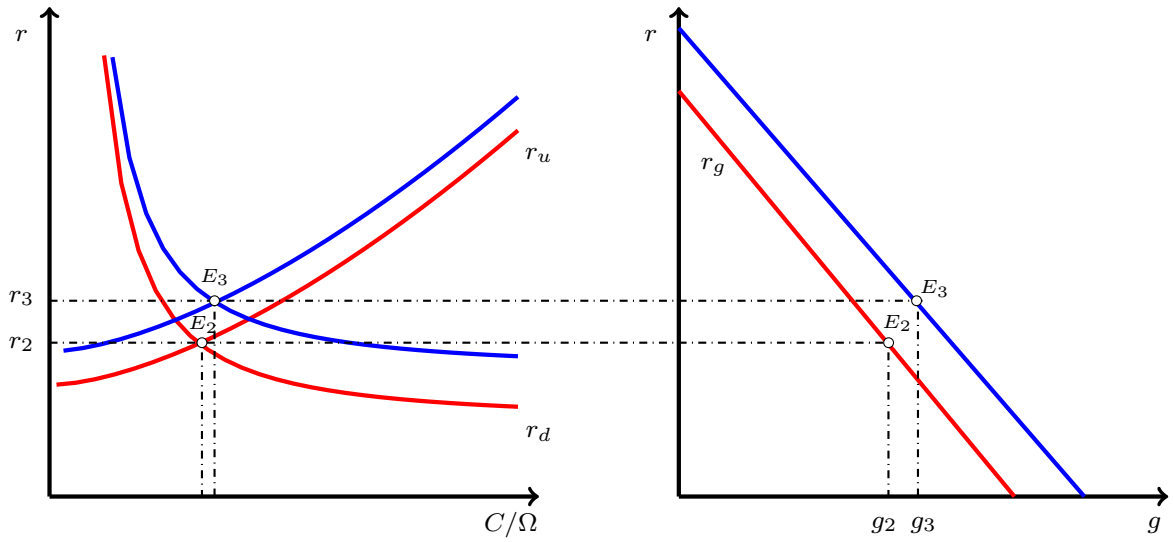


Figure 3: The effects of medical progress on r and g. Top panel: The 2^{nd} stage of the epidemiological transition. Bottom panel: The early 3^{rd} stage of the epidemiological transition.

locus shifts a little (red line), the increase in the interest rate, r, is accompanied by a decrease in the economic growth rate, which becomes equal to g_2 (the E_2 equilibrium). Instead, if the r_g locus shifts up more markedly (blue line), we observe an increase in the growth rate (from g_1 to g_3). Compared to the initial E_1 equilibrium, both the interest rate and the economic growth rate are higher in E_3. In the 2^{nd} stage of the epidemiological transition, it is likely that equilibrium

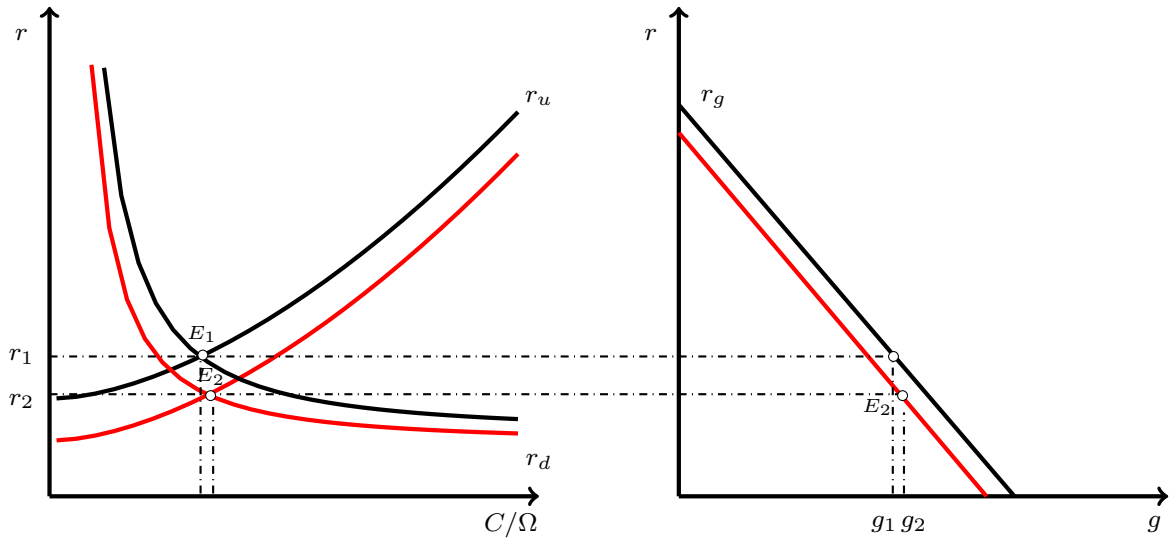
E_2 will be attained because the reduction in child and early-life mortality increases the share of young individuals, which results in a decrease in the average age and a consequent reduction in average research productivity.[10] Overall, this implies that economic growth slows down during that stage and the economy moves from equilibrium E_1 to E_2. However, starting with the 3^{rd} stage of the epidemiological transition, medical progress reduces mortality at older ages such that $\partial\mu/\partial M < 0$. This leads to an increase in the average age of the population and, thus, a rise in research productivity. At the same time, the reduction in mortality incentivizes people to save, which mitigates the upward pressure on the equilibrium interest rate. Altogether, these results imply a strong upward shift of the r_g locus, leading the economy to move to equilibrium E_3 as illustrated in the bottom panel of Figure 3. At the same time, the reduction in mortality incentivizes people to save, which mitigates the upward pressure on the equilibrium interest rate. Altogether, these results imply a strong upward shift of the r_g locus, leading the economy to move to equilibrium E_3 as illustrated in the bottom panel of Figure 3. This implies that the economic growth rate rises to $g_3 > g_1 > g_2$.

The late 3^{rd} and 4^{th} stages of the epidemiological transition

During the late 3^{rd} and 4^{th} stages of the epidemiological transition, medical innovation leads to a further increase in longevity, while child mortality is already very low. Thus, $\partial\mu/\partial M < 0$ but $\partial n/\partial M$ becomes smaller and eventually close to 0. The healthcare utilization channel starts to play a crucial role, where we have $\partial h/\partial M > 0$. Figure 4 provides a graphical illustration of the effects of medical progress on r and g. Since $\partial\mu/\partial M < 0$ and $\partial h/\partial M > 0$, an increase in the level of medical technology, M, shifts the r_d locus down. Moreover, taking into account that $\partial h/\partial M > 0$, the r_u locus also shifts down when the level of medical technology, M, increases. Since both equilibrium loci move downwards when medical technology improves, it follows that the impact of medical progress on the interest rate, r, is negative (whereas that on the ratio C/Ω is ambiguous). The r_g locus shifts down when h increases with an ambiguous impact on the rate of economic growth. As before, two equilibria can emerge: E_2 in the top panel and E_3 in the bottom panel of Figure 4. In the late 3^{rd} stage of the epidemiological transition, average research productivity, ν, is still on the non-descending part of its age gradient, which limits the downward shift in the r_d, r_u, and r_g loci. If the r_g locus shifts only little (red line), the decrease in the interest rate, r, is accompanied by an increase in the economic growth rate, which becomes equal to g_2 (the E_2 equilibrium) in the top panel. In the 4^{th} stage of the epidemiological transition,

[10] An alternative interpretation is that an increase in the population growth rate mainly raises the share of young people in an economy. Since young individuals do not yet participate in the labor market, this leads to an inverse demographic dividend (Bloom et al., 2003). The way we can capture such an inverse demographic dividend in the model is via the reduction in average productivity.

Top panel



Bottom panel

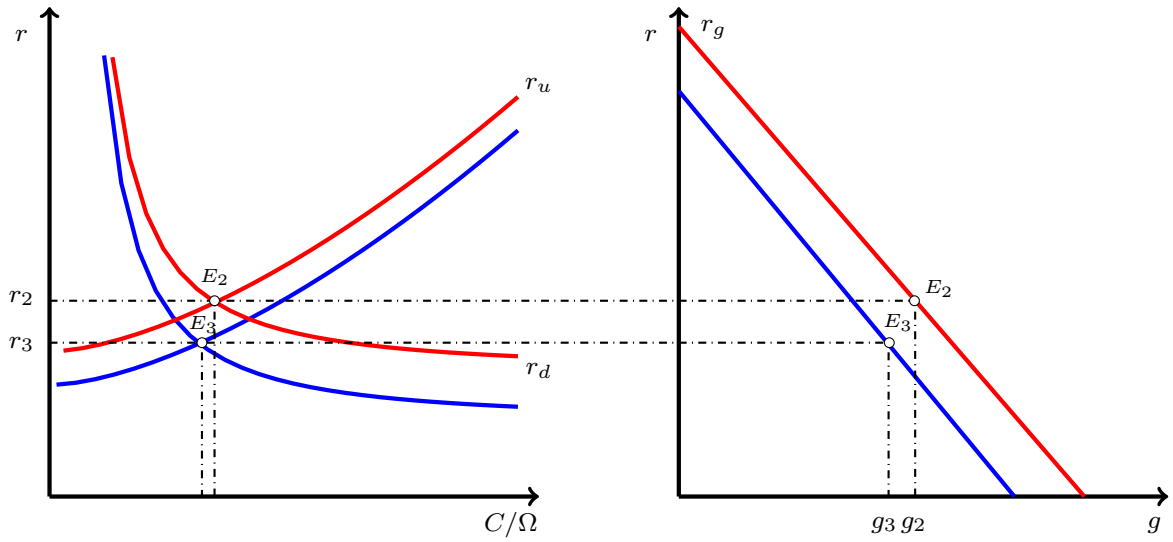


Figure 4: The effects of medical progress on r and g. Top panel: The late 3^{rd} stage of the epidemiological transition. Bottom panel: The 4^{th} stage of the epidemiological transition.

however, average research productivity ν decreases, which reinforces the downward shift in the r_d, r_u, and r_g loci. In addition, the 4^{th} stage of the epidemiological transition is characterized by a significant impact of medical innovation on healthcare consumption (the derivative $\partial h/\partial M$ is large). Thus, a marked downward shift of the three loci r_d, r_u, and especially r_g (blue line) occurs. In this case, the economic growth rate decreases (from g_1 to g_3) as depicted in the bottom

panel. Compared to the initial E_1 equilibrium, the interest rate and the economic growth rate are both lower in E_3.

Table 2: Effects of medical innovation by stage of the epidemiological transition.

Stage	Share of the working age population	$r(t)$	$h(t)$	$\nu(\bar{\tau})$	$g(t)$	Economic effects
2^{nd}	$\downarrow$	$\uparrow$	-	$\downarrow$	$\downarrow$	Rising share of young people
3^{rd}	$\uparrow$	first $\uparrow$, later $\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	Labor force expansion and capital accumulation
4^{th}	$\downarrow$	$\downarrow$	$\uparrow\uparrow$	$\downarrow$	$\downarrow$	Resource-intensive medicine

Notes: $r(t)$ represents the interest rate, $h(t)$ denotes healthcare spending as a share of wage income, $\nu(\bar{\tau})$ refers to research productivity depending on the average age $\bar{\tau}(t)$, and $g(t)$ indicates the growth rate of per capita GDP.

We summarize the effects of medical innovation on different outcome variables, differentiated by the three stages of the epidemiological transition, in Table 2. Taken together, these effects give rise to empirically testable predictions that we describe in Subsection 2.11.

2.10 Numerical illustration from the perspective of a single country

In Table 3, we illustrate the effects of medical innovation numerically across the stages of the epidemiological transition. To this end, we adopt the perspective of a single country that we follow over time. The purpose of this illustration is to show the dynamics as they are displayed qualitatively in Figures 3 and 4 and in Table 2. We do not aim to calibrate the model to fit the data of a particular country, which—due to the stylized nature of such a long-run economic model and the many idiosyncratic events that countries are confronted with over time—would be a futile attempt. Instead, we empirically test the model's central predictions in Section 5, relying on data of several countries for the time span of 1890-2018.

For our numerical illustration, we assume that $\alpha = 1/3$ and $\rho = 0.03$, which are conventional values for these parameters in the literature on economic growth. Furthermore, we assume that we start with $h \approx 0$, $n = 0.5\%$, $\mu = 3.5\%$ (leading to a life expectancy at age five of 29 years) and $\nu = 0.15$ in the baseline case to get a reasonable growth rate of the economy.

When simulating the effects of medical progress in the 2^{nd} stage of the epidemiological transition, we assume, broadly in line with data for the US during that period, a decrease in child mortality such that population growth rises to $n = 2\%$ and a decline in mortality to $\mu = 3\%$.

Table 3: Effects of medical innovation on economic growth, numerical illustration

Stage	$\nu(\bar{\tau})$	$h(t)$	$n(t)$	$\mu(t)$	$1/\mu(t)$	$\bar{\tau}(t)$	$g(t)$	$r(t)$	$C(t)/\Omega(t)$
Baseline	0.15	0	0.005	0.035	29	25	0.54%	5.32%	14.60%
2^{nd}	0.12	0	0.02	0.03	33	20	0.44%	5.85%	12.44%
3^{rd} (early)	0.18	0.15	0.015	0.02	50	29	1.75%	6.02%	13.89%
3^{rd} (late)	0.20	0.25	0.01	0.015	67	40	1.87%	5.88%	13.43%
4^{th}	0.15	0.35	0.005	0.01	100	67	0.11%	3.71%	9.91%

Notes: $\nu(\bar{\tau})$ refers to research productivity depending on the average age $\bar{\tau}(t) = 1/[n(t) + \mu(t)]$, $h(t)$ is healthcare spending as a share of wage income, $n(t)$ refers to population growth, $\mu(t)$ denotes the mortality rate such that its inverse $1/\mu(t)$ represents life expectancy for surviving children, $g(t)$ is the growth rate of per capita GDP, $r(t)$ is the interest rate, and $C(t)/\Omega(t)$ is the ratio of aggregate consumption to aggregate assets.

These parameter changes imply an increase in life expectancy at age five to 33 years and a reduction in the average age of the population to 20 years. As the average age of the population decreases and moves further away from peak productivity years in science, the demographic shifts induce a decrease in average research productivity to $\nu = 0.12$. Overall, the economic effect results in an increase in the interest rate and a decrease in the growth rate, exactly as illustrated in the top panel of Figure 3.

When simulating the effects of medical progress in the early 3^{rd} stage of the epidemiological transition, we assume, again in line with the data, that the effect of mortality reduction on child mortality starts to wane and fertility starts to decrease, such that population growth falls to $n = 1.5\%$. Concurrently, healthcare utilization starts to rise to $h = 15\%$ of wage income, and mortality falls to $\mu = 2\%$, which implies an increase in life expectancy to 50 years of age. The average age of the population increases as a result to 29 years, which implies a rise in average research productivity as compared with the previous two scenarios. As a result of the shifts, both economic growth and the interest rate rise, which is in line with the illustration in the bottom panel of Figure 3.

In the late 3^{rd} stage of the epidemiological transition, we assume, in line with the data, that medical progress raises healthcare utilization to $h = 25\%$, mortality shrinks to $\mu = 1.5\%$, resulting in an increase in life expectancy to 67 years, and the population growth rate falls to $n = 1\%$. This implies that the average age of the population reaches 40 years, which is close to the peak of research productivity depending on age found in the literature (Jones, 2010). Thus, research productivity rises further to $\nu = 0.2$. Overall, these changes imply a further increase in economic growth but also a decrease in the interest rate, which is in line with the prediction for this stage of the epidemiological transition as displayed in the top panel of Figure 4.

Finally, in the 4^{th} stage of the epidemiological transition, we assume that further medical progress raises healthcare utilization to $h = 35\%$, mortality falls to $\mu = 1\%$, implying a life expectancy of 100 years, and population growth decreases to $n = 0.5\%$. This leads to a rise in the average age of the population to 67, far above the age of peak research productivity, resulting in a decrease to $\nu = 0.15$. Overall, this implies a fall in economic growth and in the interest rate, which is consistent with the illustrations for the 4^{th} stage of the epidemiological transition as shown in the bottom panel of Figure 4.

2.11 Testable predictions

We are now able to state the testable predictions for the empirical part of the paper. From Figures 2–3 and Tables 2–3, the following two testable hypotheses can be derived.

Hypothesis 1. *There is a causal pathway from medical innovation to economic growth. An important transmission channel is the effect of medical innovation on expanding life expectancy.*

Hypothesis 2. *The overall effect of medical innovation on economic growth is non-linear. Medical innovation has the potential to either increase or decrease economic growth, depending on the epidemiological background. We can distinguish between the following cases:*

- *For countries in early stages of development (2^{nd} stage of the epidemiological transition), medical innovation stifles economic growth.*
- *For countries in intermediate stages of development (3^{rd} stage of the epidemiological transition), medical innovation fosters economic growth.*
- *For countries in late stages of development (4^{th} stage of the epidemiological transition), the positive economic growth effect of medical innovation weakens and eventually becomes negative.*

We move on to describe the empirical models by which we test the two hypotheses in Section 3, present the data and summary statistics in Section 4, and report the results of the empirical analysis in Section 5.

3 Empirical analysis

Based on the predictions of the theoretical model, we conduct regression analysis to identify the causal linkages between medical innovation, longevity, and income per capita. The analysis is developed in two main parts, namely an event analysis and a structural regression.

3.1 Event analysis

In the first step, we perform an event analysis to assess the impact of the introduction of medical innovations on income per capita within our sample of countries, controlling for various econometric issues and confounding factors, which are detailed below. Specifically, we quantify the effect of the introduction (launch) of medical innovations as resulting from the first patent filing at the United States Patent and Trademark Office (USPTO). For each country, we assume the year of the first patent application in medical fields to be the start of the treatment and the country to remain treated from then on (full absorption condition). Our identification strategy is based on the idea that countries capable of seeking patent protection for their innovations at the USPTO have reached a certain threshold of knowledge to effectively utilize advanced healthcare-related technologies, regardless of whether they are developed domestically or abroad. This would result in an increase in life expectancy and, in turn, in the level of GDP per capita. Indeed, the development of medical innovations depends on internal technological capabilities and on how firms (as well as the public sector) in a country respond to the population's demand for healthcare.

In the event analysis, our baseline equation is

$$Y_{it} = \alpha_{0i} + \alpha_1 \cdot E_{it} + \alpha_2 \cdot Z_{it} + \alpha_t + \epsilon_{it}, \tag{8}$$

where the outcome variable, Y_{it}, is GDP per capita in country i in year t, E_{it} is a binary indicator of unitary value from the year of the first filing onwards and zero otherwise (treatment $\times$ post). α_{0i}'s identify country fixed effects capturing the impact of un-observable characteristics that do not vary over time, α_t refers to a set of time dummies that collect the effects of co-movements caused by un-observable factors (technology shocks, globalization, changes in the institutional setting, etc.), and ϵ_{it} represents a spherical error term. To address the issue of omitted variables, we employ Z_{it} as a vector of control variables, which includes key factors identified by standard growth theory as drivers of income, such as the stocks of physical assets and industrial innovations per inhabitant.

We estimate the Difference-in-Differences specification in Eq. (8) as Local Projection (LP-DiD) regression following Dube et al. (2023). This amounts to expressing Eq. (8) in first differences and assessing the forward increases in the outcome variable h years after the realization of the event at time t (with $h = 1, 2, ..., H$):

$$Y_{it+h} - Y_{it-1} = \alpha_1^h \cdot \Delta E_{it} + \sum_{j=1}^{J} \alpha_{2,j} \cdot \Delta Z_{it-j} + \sum_{j=1}^{J} \alpha_{3,j} \cdot \Delta Y_{it-j} + \sum_{j=-J}^{h} \alpha_{4,j} \cdot \Delta E_{it+j} + \alpha_t + \varepsilon_{it}. \tag{9}$$

The LP-DiD regression utilizes lagged values of the dependent variable from the original specification (Eq. (8)) to address selectivity issues, as richer countries, where available income is

higher and the population demands more healthcare, may engage in medical innovation earlier and self-select into the treatment group. We also include lags of the treatment to control for dynamic effects of this variable because GDP per capita may respond with a delay to the launch of medical innovation. Conversely, leads of the treatment variable serve to exclude anticipation effects because income per capita may change prior to the introduction of medical innovation (at time t). This may happen when individuals adjust their investment decisions, thereby influencing income levels, in anticipation of better health conditions resulting from medical innovations. This phenomenon might also have occurred in the earlier stages of our time horizon when medical innovations were episodic and random, and the adoption of new medical treatments commenced before these innovations were patented.

In Eq. (9), α_1^h represents the single-year value of the average treatment on the treated (ATT) effect, which we will illustrate through an event-analysis plot below. If the assumption of pre-treatment parallel trends between the treated and control units is satisfied, the departure of α_1^h from zero would quantify the single-year increase in GDP per capita (expressed in dollars) attributable to medical innovation.

It should be observed that the forward increase in GDP per capita with respect to its pre-treatment trend uses the average of the outcome variable over a ten-year interval before the event ($\sim Y_{it-1}$). This makes the pre-event value of GDP per capita less sensitive to outliers, ensuring more accurate estimates compared to the use of single-year values. Also, the number of years after the treatment may vary significantly across countries; hence, to mitigate the impact on ATT of countries with a low number of post-event time points, we re-scale the single-year values of the treatment coefficient with a frequency weight inversely proportional to the number of time points used for its computation.

There are two characteristics of our data, which are worthy of discussion here. First, our sample is made up by a group of industrialized countries observed for over a century, and all of them file at least one patent related to medical innovation (pharmaceuticals, medical equipment, etc.) at the USPTO in the time horizon of our analysis, although in different years. This implies that our treatment regression model is staggered and, more importantly, that all countries enter the treatment group at a given point in time. Our regression procedure takes into account this dimension of the data by comparing, for each year within the time interval, the change in income per capita between the units that have been treated and those that have not been treated but will be treated later on. In other words, the group of control units used in the DiD regression changes each year, consisting of the 'switchers' only (i.e., units that have not yet been treated).

To assess whether this condition affects our results, as a robustness check, we replicate the LP-DiD regression using a larger sample of countries extracted from a different source covering

the world as a whole. Although for these countries data are available only for a shorter period of time, with this sample, we are able to build a control group that includes both 'not-yet-treated' and 'never-treated' units; the latter are countries that have no patent applications in the medical field at the USPTO.

Second, we may question whether the year of introduction of medical innovation (i.e., the launch of the first medical patent) can be considered as a valid treatment by fulfilling all identification criteria discussed above (selection, anticipation effects, etc.). The usage of this identification assumption is a common practice in the microeconomic literature examining the impact on different dimensions of performance associated with the transition to a new technology (see Czarnitzki et al., 2023, Alderucci et al., 2020). At the macroeconomic level, similar procedures, based on treatment analysis, have been used to study the effect of democratization on economic development (Acemoglu et al., 2019). Note that if our identification strategy is grounded, we should expect to observe similar or even greater increases in GDP per capita when the threshold of the achieved technology base used to consider a country as treated is raised to higher levels, rather than simply considering the launch of the first innovation (patent). Therefore, as alternative treatment variables, we will consider the year in which each country experiences the largest increase in the stock of medical patents per person (referred to as the peak year in the literature on local projections; see Jordà, 2005), as well as the year in which a country reaches the same degree of medical innovation as the US, as measured by the median or the maximum value of the per capita stock of medical patents in the US. For this specific analysis, the US is excluded from the event analysis.

3.2 Structural regression

In the second step of the empirical analysis, we identify the long-term impact of the structural drivers of GDP per capita, using the following cointegration model

$$\ln Y_{it} = \beta_i + \beta_M \ln M_{it} + \beta_A \ln A_{it} + \beta_L \ln L_{it} + \lambda_i \ln F_t + \epsilon_{it}, \tag{10}$$

where Y is GDP per capita, β_i is the country fixed effect, M is medical innovation, A is industrial innovation, L is longevity, and F identifies un-observable factors (shocks) that have asymmetric effects across countries, here captured by λ_i's. The long-run effect of the right-hand side variables in Eq. (10) is derived from the short-run parameters of a dynamic panel regression model. Specifically, we re-formulate Eq. (10) as an Auto-Regressive Distributed Lag specification and estimate it with the Cross-Sectionally augmented estimator devised by Chudik and Pesaran (2015) (CS-ARDL). Our empirical specification, expressed in general terms, is therefore given by

$$y_{it} = \gamma_i + \gamma_1 y_{it-1} + \gamma_2 x^k_{it} + \gamma_3 x^k_{it-1} + \lambda_i f_t + \epsilon_{it}, \qquad \beta_k = \frac{\gamma_2 + \gamma_3}{1 - \gamma_1}, \tag{11}$$

where lowercase letters denote the natural logs of the variables, $y = \ln Y$, $x^k = \ln X^k$, with X denoting the vector of regressors ($k = M, A, L$), and $f = \ln F$ is measured through the cross-sectional means of all the variables in the model (Common Correlated Effects, CCE; Pesaran, 2006). The parameter β_k refers to the long-run impact of the explanatory variables in Eq. (10). In the main text below, we report the long-run (cointegration) elasticities that we obtain by estimating Eq. (11), as well as γ_1, which measures the speed of adjustment of variables towards equilibrium.

Compared to the main procedures commonly used in the literature (static and IV regressions), our estimation procedure controls for the dynamic adjustment of variables, and accounts for the starting disparities in longevity, which have been found to drive much of the differences in prior works (Aghion et al., 2011, Bloom et al., 2014). The CS-ARDL regression provides consistent estimates regardless of the integration order of the variables and is less susceptible to reverse causality issues than other estimators, provided that the lag structure of the variables is correctly specified. For the sake of notational simplicity, Eq. (11) uses one-year lags; empirically, the number of lags is selected using the rule-of-thumb formula $p = T^{1/3}$, where T is the number of periods in the estimation. To validate the soundness of our regression procedure, we report the results of the tests on the presence of unit roots, cointegration, residual cross-sectional dependence, and causality in Appendix B (see Tables B8-B10). The last condition, which is crucial for interpreting cointegration estimates, is verified through a set of weak exogeneity tests. These findings indicate that the causation runs from x^k to y.

4 Data and summary statistics

The analysis is conducted by matching various data sources. The first dataset includes historical data from 1890 to 2018 offering baseline information on income, innovation activities, life expectancy, and a set of other factors (confounders) that may have driven income increases in the last century. The second dataset covers the same group of countries with historical data but is shorter, spanning from 1981 onwards. It contains alternative measures of innovation and a larger group of control variables. The third dataset covers a global sample of countries from 1950 onward but offers insights only on a limited number of variables.[11]

Historical data on income, capital, employment, population, etc., is taken from the Long-Run Productivity Dataset (Bergeaud et al., 2016; release August 2020). GDP per capita is expressed in US dollars at constant prices as of 2015 and is adjusted for purchasing power. Longevity is

[11]The first and the third sources are used in the event analysis. The first and the second sources are used in the cointegration analysis.

expressed in terms of life expectancy at birth and is extracted from the 'Our World in Data' dataset (Roser, 2022). Innovation is mainly measured in terms of patent counts using data from the Comprehensive Universe of U.S. Patents (CUSP) dataset (Berkes, 2018). This includes information on patent applications at the United States Patent and Trademark Office (USPTO), distinguished by year of application, country of assignee, and technology (IPC) class. The dataset provides a consistent series of patent applications from 1836 to 2010, which are extended until 2018 using data from OECD Statistics on USPTO Patent Applications by technology (hereafter denoted as OECD-SPA).

We identify two primary patent categories: medical patents and industrial patents. Medical patents are those falling under the International Patent Class (IPC) A61 of the World Intellectual Property Office (WIPO), encompassing medical equipment and pharmaceuticals. Industrial patents are defined residually as those patents that do not fall under the category of medical patents.

In robustness checks, but limited to the period from 1981 onwards, we use data from the OECD-SPA dataset on patent applications at the European Patent Office (EPO) and applications filed under the Patent Cooperation Treaty (PCT). For this shorter time interval, we also consider a measure of innovation effort made in medical fields, based on data on R&D expenditures (source: OECD-SPA, R&D by sector and major field, FORD). All our measures of innovation are defined as cumulative numbers of patent applications (i.e., stocks) and are calculated using the perpetual inventory method with a geometric depreciation rate of 15%. To build R&D stocks, we capitalize research expenses expressed in real US dollars adjusted for purchasing power. To eliminate scale effects, all stock variables are expressed as a ratio to the population.

To avoid omitted variable biases, we include a broad set of controls: (i) physical capital per person (source: Long Term Productivity database); (ii) human capital (source: Barro-Lee database); (iii) government size (source: Macrohistory database); (iv) financial development (source: Macrohistory database); (v) trade openness (source: Macrohistory database); (vi) foreign knowledge spillovers (source: own computations; see below for details); and (vii) total health expenditures as a share of GDP (only from 1981 onwards; source: OECD). The per capita stock of physical capital is obtained by multiplying the capital stock per hour worked by the number of hours worked per worker. Human capital is expressed as the average number of years of tertiary education in the population aged 15-64 years. The data release of 2021 of the Barro-Lee dataset allows historical series for the period 1820-1945 to be integrated with post-WWII data from Barro and Lee (2013). Our index of human capital is available at five-year intervals from 1890 to 2010 and, accordingly, we interpolate values for intermediate years. Human capital is used as a control variable to ensure that the impact of innovation (medical and non-medical) is not confounded with

that of education, which is another key driver of economic growth according to most economic growth theories.

The Macrohistory database developed by Jordà et al. (2016) provides data on the GDP share of public debt (our proxy for government size), the credit to the private (non-financial) sector (our proxy for financial development), and the value of exported goods and services over GDP (trade openness). We control for government size to exclude the impact of medical innovation being confounded with the effect of the expansion of public expenditures related to increasing longevity and aging, such as rising spending on healthcare and pensions (note that the latter data are available only from the late 1960s onwards). The private credit-to-GDP ratio is used to filter out the effect of financial development, which is a key enabler of all investment types, especially those based on riskier and/or longer-term projects. Trade openness is introduced to filter out productivity gains, and the resulting income increases associated with the rising scale of production. Moreover, we construct measures of international technology spillovers, induced by knowledge developed in the area of medical and industrial technologies. Our spillover variables are obtained as the weighted stock of foreign patents. To address reverse causality issues (e.g., bilateral trade may reflect differences in income levels across countries), we define weights as the inverse distances between pairs of countries (Madsen et al., 2021). Geographical distances (in kilometers) are taken from the Geo-Dist dataset (Mayer and Zignago, 2011). As the primary measure for constructing the weight, we use distances that reflect the population concentration in the main agglomerations of each country. We also assess the sensitivity of our results by utilizing simple inverse-distance measures or inverse population-weighted distance with exponential (quadratic) decay. The latter should capture the fact that knowledge dissemination becomes difficult beyond certain distance thresholds (Lychagin et al., 2016). Controlling for distance is important, given the evidence that advancements in medical technologies and healthcare systems result in positive knowledge spillovers through the sharing of medical service treatments, etc. (Chandra and Staiger, 2007, Baltagi and Yen, 2014).

In the event analysis, we utilize the Penn World Table (release 10) to build a control group that also includes 'never-treated' companies. This source allows us to broaden the sample coverage to 127 countries. Additional details regarding this data are briefly outlined below.

The sample of countries covered by our historical analysis includes Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Sweden, Switzerland, UK, and the US. Our data offers the advantage of tracking the changing role of medical innovation along the path of economic development and rising longevity. One caveat is that the availability of the data is endogenous to the development of countries (affecting the quality of record keeping), with the risk of offering an overview on a

selected group of economies; this, however, is a feature commonly shared by all studies using macro-historical data. Descriptive statistics for the entire sample and by country are available in Tables B1 and B2 in Appendix B.

5 Results

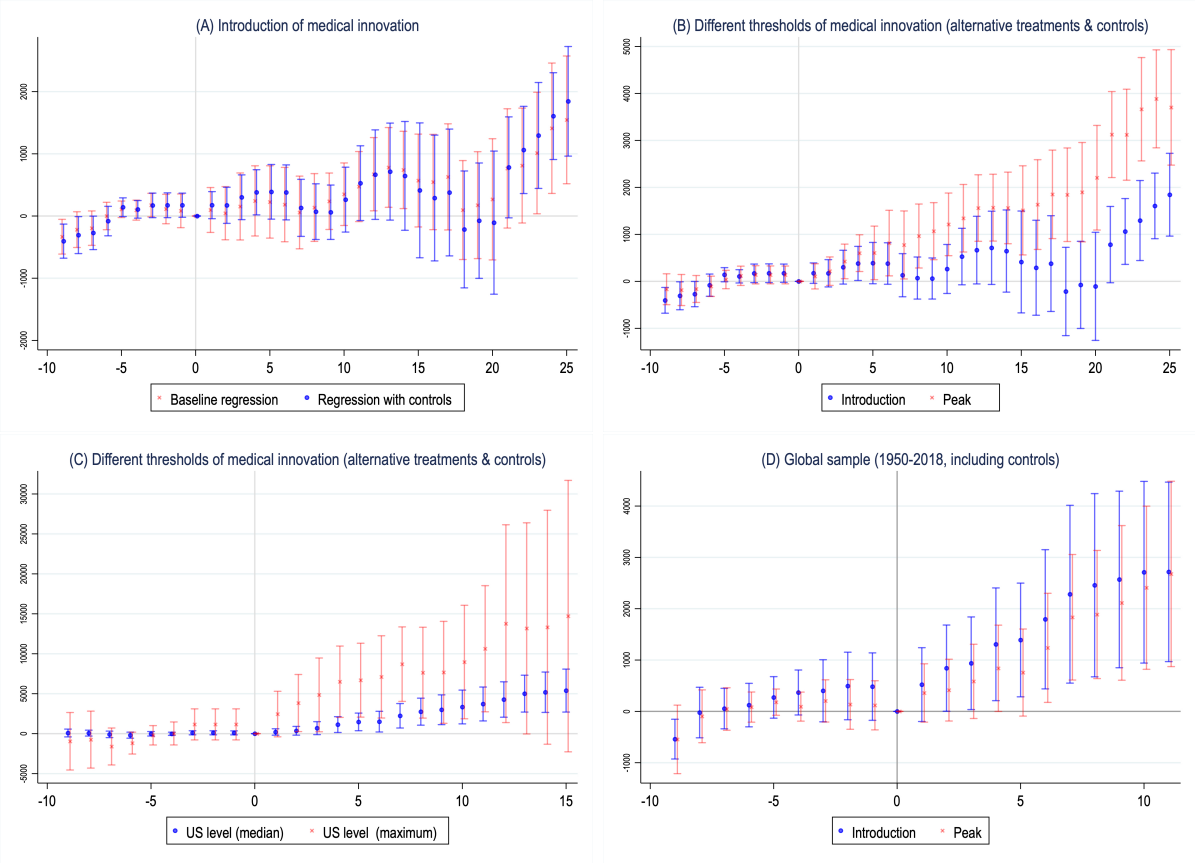
5.1 Preliminaries: causality and dynamic properties of the empirical model

To test Hypotheses 1 and 2, we need to ascertain whether the data support the idea that, even after controlling for industrial innovation, income per capita, longevity, and medical innovation have a structural relationship, and that causality runs from medical innovation (via longevity) to GDP per capita. In this respect, we first run a set of panel unit root tests to determine the integration order of the variables. Afterward, we perform cointegration tests to ascertain the presence of a stationary (long-run) equilibrium relationship among our variables. Then, to assess the direction of causation, we test the (weak) exogeneity condition using a panel Vector Error Correction regression in which each of the variables mentioned above is regressed against the lagged changes observed in all variables of the model, along with the residuals of the cointegration relationship (see Eberhardt and Presbitero, 2015). The results of these tests indicate that a stationary, long-run relationship exists between income per capita, medical innovation, and longevity. Moreover, the direction of causation mostly runs from the variables on the right-hand side of Eq. (11) to GDP per capita. In our cointegration analysis, we account for the effect of strong cross-sectional dependence caused by un-observable common factors. In Appendix B, we show that there is no unaccounted cross-sectional dependence in the cointegration residuals, implying that our estimates should be consistent. The results of all these tests are reported in Tables B8-B10 in Appendix B.

5.2 Event analysis

The findings of our event analysis are illustrated in Figure 5. In Panel (A), we utilize historical data going back to 1890 for 19 countries (excluding the US) to examine the impact of medical innovations on GDP per capita up to 25 years after their introduction. The graph presents two plots: one (red crosses) represents the results of a baseline regression without controls, while the other (blue dots) represents the outcome obtained from the full specification with control variables in Eq. (9). Each plot illustrates the change in income levels, measured in real US dollars per person and the associated 95% confidence interval (vertical bars). The lack of significance in

Figure 5: Event-analysis results: Response of GDP per capita to medical innovation



Notes: The graph illustrates the change in GDP per capita (in constant US$ at 2015 prices and PPP) to medical innovation treatment. The responses are estimated from a set of Local Projection Difference-in-Differences specifications (Eq. (9)). The specification includes time dummies and utilizes three-year lags of outcome variable (selection control), per-capita stocks of physical capital and industrial patents (control of omitted variables), and treatment variable (dynamic adjustment control), as well as h forward values of treatment (control of anticipation effects). Standard errors are clustered at the country level.

the estimates during the pre-event period suggests that the assumption of pre-treatment parallel trends is satisfied. By contrast, the significance of the coefficients following the event indicates that medical innovations have an economically relevant effect on income per capita. This impact corresponds to the value of the estimated parameter. Panel (A) demonstrates that medical innovation leads to a subsequent increase in income over the course of several years. After approximately a quarter of a century, the impact of medical innovation becomes statistically significant and economically substantial, resulting in an increase in income by $1,844 per person. When compared to the average income of our historical sample of countries ($20,222), this value corresponds to a significant 9.1% increase.

The next two graphs explore how the income response changes when we raise the innovation threshold used to determine a country's treatment status (Figure 5(B) and (C)). In Panel (B),

we compare the event plot associated with the launch of innovation (represented by blue dots) with the event plot obtained by considering the year of the peak increase of medical innovation as an event (red crosses). As expected, this regression indicates a much faster effect of medical innovation on GDP per capita, as it becomes significant within a decade from the treatment and exhibits a significantly greater magnitude. In less than twenty-five years, the income increase induced by (peak) medical innovation is twice as much as when considering the year of innovation launch, amounting to \$3,703 (an average increase of 18%). In Panel (C), we examine the impact of medical innovation on the change in income levels by analyzing the year in which a country achieves the median and maximum levels of medical innovation of the US. It is important to note that not all countries in our sample have reached these thresholds. Therefore, in this case, the analysis includes both the 'switcher' and 'never-treated' units as part of the control group. Furthermore, it is worth mentioning that the achievement of these thresholds occurred relatively late within the time frame of our study. As a result, our event analyses evaluate the response of GDP per capita over a 15-year period following the event. Within our historical sample, 15 out of 19 countries have been able to achieve the median value of the per capita stock of medical patents held by the US. For these countries, we observe a statistically significant increase in GDP per capita of \$5,391. On the other hand, Switzerland stands out as the only economy capable of reaching the maximum levels of medical innovation of the US. For this country, we estimate an income increase of \$14,715. Overall, the results in Panels (B) and (C) of our event analysis support the validity of our identification strategy, indicating that the introduction of medical innovation can be considered an effective determinant of income.

Moving on to Panel (D), we expand our analysis to a global sample of 127 countries observed from 1950 onwards. Among these economies, 59 have filed patent applications in the medical field at the USPTO. The remaining 69 countries do not have medical patents and remain within the control group. These results reveal that the increase in GDP per capita estimated for this larger sample is \$2,707, which is markedly lower than that found for the group of rich countries in Panels (A)-(C). However, in relative terms, the income response to the introduction of medical innovation that emerges from Panel (D) is quantitatively important, amounting to 32% of the average income level of the global sample of countries.

5.3 Structural estimates

Next, we conduct a long-run (cointegration) analysis and estimate a structural equation that links GDP per capita to the main factors identified by our theoretical model as income drivers (refer to Table 4). In the following section, we expand the empirical model to incorporate additional factors that were not considered in our theory but could potentially influence income evolution. Failure

to account for these factors could potentially bias the estimated impact of our main explanatory variables. The effect of all other un-measurable factors is captured by the CCE terms.

In column (1), we regress GDP per capita on the per capita stock of medical patents. When considered as sole regressor, the coefficient of this variable should capture all income-enhancing effects associated with technological advances achieved in medical fields, including effects that are channeled through increased life expectancy, as well as effects that are channeled through improvements in health that are unrelated to survival but also technological complementarity or knowledge spillovers across medical and industrial innovation. Column (2) breaks down the impact of medical innovation into that enabled by advances in medical equipment and pharmaceuticals, respectively, illustrating that both components are significantly related to income levels with a slightly higher impact of the former. In column (3), we include longevity as a regressor and find a coefficient of 1.3, which is highly statistically significant and consistent with previous research (see, among others, Cervellati and Sunde, 2011). In column (4), we identify the income elasticity of industrial innovation which, reasonably, is found to be much larger than that associated with medical innovation (0.062). Column (5) considers all explanatory variables together. This regression confirms that all explanatory variables have a significantly positive impact, although the parameter estimate for medical innovation is substantially smaller in magnitude. This finding reveals that the income effect of medical innovation is channeled through extended longevity. Nonetheless, medical innovation may also have a direct impact. This effect could be either positive due to technological complementarity and knowledge spillovers, or negative if medical innovation is associated with ineffective health care spending (Chandra and Skinner, 2012), crowding out industrial innovation as a driver of economic growth. We will revisit this issue later in the paper. From the comparison of estimates in columns (2) and (6), it emerges that the coefficient of medical equipment technologies remains largely positive and significant even with the inclusion of life expectancy, while the coefficient size of pharmaceutical innovations falls and remains only marginally significant. This suggests that medical equipment technologies are more likely to raise income by allowing for improvements in non-survival related health, such as reductions in chronic disease, disability or mobility impairments as well as by facilitating technology spillovers, while the income impact of pharmaceutical innovations mainly transmits through increases in longevity.

5.4 Robustness checks to omitted factors and other econometric issues

One possible concern is that our long-run estimates are affected by problems of omitted variables, which may lead to an overstatement of the impact estimated for our key regressors. In Table B3 of

Table 4: Health innovation and income levels: long-run estimates (CS-ARDL)

	(1)	(2)	(3)	(4)	(5)	(6)
Medical innovation	0.027***				0.004***	
	(0.001)				(0.001)	
Medical equipment		0.023***				0.011***
		(0.001)				(0.001)
Drugs		0.011***				0.002*
		(0.001)				(0.001)
Longevity			1.323***		1.600***	1.458***
			(0.048)		(0.058)	(0.056)
Industrial innovation				0.062***	0.089***	0.087***
				(0.003)	(0.004)	(0.004)
Speed of adjustment	-0.102***	-0.137***	-0.094***	-0.105***	-0.133***	-0.162***
	(0.014)	(0.016)	(0.015)	(0.014)	(0.017)	(0.017)
Obs.	2,380	2,380	2,286	2,380	2,286	2,286
R-squared	0.149	0.169	0.148	0.159	0.183	0.197
Countries	20	20	20	20	20	20

Notes: Dependent variable: GDP per capita. Long-run estimates derived from a panel CS-ARDL regression with homogeneous parameters. The data span the years 1890-2018. All variables are expressed in logs. Estimates include country-specific fixed effects and common correlated effects. Newey-West standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B, we perform a sensitivity analysis including the set of controls introduced in Section 4. We find that in all estimates, our main regressors continue to remain highly significant. A number of findings are nevertheless worth briefly discussing. In line with standard growth theories, GDP per capita is found to be positively related to the capital-labor ratio (with an elasticity of 0.06), human capital (0.12), and trade exposure (0.34), which has a large elasticity, probably reflecting the large variation of trade figures over time. The public debt-to-GDP ratio is also found to be positively related to income per capita. This finding may capture the expansionary effect of public infrastructure and other public spending (Gemmell et al., 2016). Alternatively, it may reflect co-movements between increases in per capita income and life expectancy, and the associated expansion of public expenditure for social protection over time. The latter explanation seems to be supported by the decrease in the coefficient for longevity when controlling for the public debt-to-GDP ratio in the regression. Conversely, the private credit-to-GDP ratio is negatively correlated with GDP per capita. A high private credit-to-GDP ratio can indicate that the economy is heavily

indebted. By increasing the risk of default, a high level of debt can lead to financial crises that disrupt economic activity and lower GDP per capita in the long run. The finding may also be explained by the fact that in wealthier countries, a greater proportion of savings is invested in more sophisticated financial instruments, rather than being held in deposits or used for credit.

Noteworthy, our estimates are also robust when including proxies for international knowledge spillovers.[12] A positive income effect is associated with foreign stocks of medical innovation, but a negative effect is observed for industrial innovation developed abroad. The latter finding contrasts with most of the existing literature, which suggests that the international exchange of ideas leads to higher levels of total factor productivity.[13] A few studies, however, show that negative spillover effects can arise across countries due to import competition and the fact that an increasing share of traded goods is based on technologically advanced products, whose production is increasingly geographically concentrated, reducing the scope for international knowledge transfers (Bitzer and Geishecker, 2006, Venturini, 2015). The difference between our findings and the majority of the results in the literature on industrial technology spillovers may also be attributed to the composition of our sample and/or our use of income per capita as the dependent variable, instead of Total Factor Productivity.

For a shorter time interval (1981-2018) we are able to perform a finer sensitivity analysis, where we use the per capita stock of medical R&D, or the per capita stock of patent applications filed at the EPO or obtained under the PCT, as indicators of medical innovation. Over this time period, we can also control for health expenditures, expressed as a ratio of GDP. All of these estimates confirm the main pattern of our results (see Table B4 in Appendix B).[14]

We also evaluate the impact of using longer data intervals on the accuracy of our estimates. In essence, instead of conducting regressions on yearly observations, we estimate the model using data taken at non-overlapping five-year intervals. Specifically, we run both a static and dynamic specification (the latter being formulated as an ARDL(1,1)) augmented with country-specific

[12]Since spillover variables are computed as weighted means of foreign innovation stocks, we do not include CCE terms (i.e., un-weighted means) of these regressors in such estimations. See Eberhardt et al. (2013) for a discussion of the identification of international knowledge spillovers in cross-country studies characterized by strong cross-sectional dependence due to common unobservable factors.

[13]To assess whether the evidence regarding the cross-border income effects of foreign medical technology is influenced by the distance-based weighting scheme utilized, we also provide estimates based on simple inverse-distance weights for foreign knowledge and population-weighted inverse distance weights in Table B3 of Appendix B. These results are fully consistent with our main findings.

[14]Notably, medical innovation becomes insignificant in the regression with longevity, but only if we do not control for health expenditure. The latter has indeed a strong and direct negative impact on per capita GDP, which is likely reflected in the coefficients on medical innovation and longevity if the health expenditure variable is excluded. This is, again, consistent with the mechanisms present in the model.

fixed effects and CCE terms. These estimates should be less sensitive to the impact of common, short-term shocks and mitigate the attenuation bias associated with classical measurement errors in the explanatory variables. These errors could be due, for instance, to the time lag between the priority date and the application date (or the granting date) of the innovation. One disadvantage of using data over longer time intervals is that the empirical model may not be entirely immune to reverse causality, which can result in upward biased estimates for the explanatory variables. This seems to emerge from the estimates of five-year data intervals, which are reported in Tables B5 and B6 in Appendix B. In both types of estimates, the parameters for medical innovation and longevity are significantly larger than those presented in Table 4. This suggests that long-run estimates based on annual data are highly reliable.

5.5 Quantification of effects

Using the long-run elasticities in Table 4 as a reference (column (5)), we can quantify the rise in income levels resulting from plausible changes in our key variables. Based on our estimates, an additional patent in the medical field (per person) would result in a 0.1 percent increase in income per capita in the long run. By contrast, a one-year increase in life expectancy would boost income per capita by 2.4 percent, a finding that is broadly in line with earlier studies on the macroeconomic effects of health (see, e.g., Bloom et al., 2004; Aghion et al., 2011).

We can also determine the rise in income per capita associated with a standardized increase in medical innovation, as measured by the stock of medical patents, by disentangling the effect channeled by longevity from that transmitted by other mechanisms, such as spillovers. The gross income effect (including the longevity channel) induced by a standard deviation increase in medical innovation can be quantified as a 0.089 absolute change in GDP per capita ($0.089 = 0.027 \times 3.3$, where 0.027 represents the estimated elasticity and 3.3 is the natural log of the standard deviation in medical innovation, namely 27.5 patents per person, as reported in Table B1). If we express this value as a proportion of GDP per capita ($20,222$ dollars on average), income per capita would increase by 1,809 US$ ($1,809 = 0.089 \times 20,222$). Reassuringly, this value is extremely close to the income increase obtained from the event analysis. As shown in column (5) of Table 4, most of this impact is conveyed through the increase in longevity. Therefore, the direct impact of medical innovation on income is much smaller, equal to 268 US$ ($= 0.004 \times 3.3 \times 20,222$).

5.6 Non-linearities

Another key finding in Section 2 (Hypothesis 2) is that medical innovations translate into higher income levels only for countries in the 3^{rd} stage of the epidemiological transition (see also, among others, Bhargava et al., 2001). For these countries, the benefits of faster population growth and higher savings outweigh the negative effects of costly healthcare and potential increases in the interest rate. In the earlier stages of the epidemiological transition, medical innovations mainly lead to a faster growth of the non-working age population, while the interest rate rises. Both effects together imply a negative impact of medical innovation on per capita GDP growth, which is consistent with the findings by Cervellati and Sunde (2011). In later stages of development, i.e., particularly in the 4^{th} stage of the epidemiological transition, medical innovation features decreasing returns, which can be viewed as an extended form of 'flat-of-the-curve medicine'. While the original notion advanced by Fuchs (2004) can be read as decreasing returns of treatment intensity for a given state of medical technology, our analysis focuses on the crowding-out effect of medical innovation on productive resources. Indeed, to the extent that medical innovations expand longevity and increase the demand for medical care, this diverts resources from production and R&D activities. At that stage, income may once again start to have a negative relationship with medical innovation.

In this section, we delve into Hypothesis 2, and examine whether our results reflect the non-linear relationship between life expectancy and GDP per capita, as suggested by Figure 1. The results of our analysis when allowing for stage dependencies and non-linearities, respectively,are shown in Table 5. First, we conduct regressions when categorizing the sample into various groups of countries based on their stage of the epidemiological transition at the beginning and end of the sample period, which is approximately around the 1920s and 1970s, respectively. Second, we examine in greater detail the interplay between medical innovation and longevity, seeking to pinpoint the age threshold at which medical innovation begins to have a positive impact on GDP per capita.

In columns (2) and (3), we divide the sample into countries with a life expectancy at birth below and above 50 years before 1920, and then run the regression using data from 1920 to 2018. This age threshold aligns with the transition threshold between the 2^{nd} and the 3^{rd} stage of the epidemiological transition (Omran, 1998). More than half of the countries in our sample met this condition at the start of the twentieth century (11 out of 20 countries), while the other half surpassed this threshold only more recently.[15] We can compare these estimates with the

[15]The group of 3^{rd} stage transition countries in 1920 includes Australia, Canada, Denmark, Ireland, Netherlands, Norway, Sweden, Switzerland and the USA. The group of 2^{nd} stage transition countries includes Austria, Belgium, Chile, Germany, Finland, France, Italy, Japan, Mexico, New Zealand, and the UK.

benchmark estimates obtained for the entire sample in column (1). The table shows that the long-run impact of longevity is similar across country groups. The effect of medical innovation, however, is positive only for the group of countries that have completed the transition to the 3^{rd} stage of the epidemiological transition at the beginning of the sample period, whereas it is negative for the other set of countries.

To support the prediction of our theory that medical innovations only raise income levels as long as the workforce is not too old, i.e., before transitioning from the 3^{rd} to the 4^{th} stage of the epidemiological transition, we run the regression for countries with a life expectancy below 70 years between 1950 and 1970 separately from those with a life expectancy exceeding 70 years. The former group would identify countries that were still in the 3^{rd} stage of the epidemiological transition in the last quarter of the twentieth century (column 4), while the latter group had already transitioned to the 4^{th} stage (column (5)).[16] These regressions use time observations from 1970 onwards, yielding results that are consistent with those in columns (2) and (3): longevity appears to be insignificant for both country groups, while the coefficient of medical innovation is positive for countries in the 3^{rd} stage of the epidemiological transition but not for those that have already transitioned to the 4^{th} stage.

Results similar to columns (2) and (3) are also obtained when running a regression on the total sample, but with the inclusion of an interaction term between medical innovation and a dummy variable for countries that progressed from the 2^{nd} to the 3^{rd} stage of the epidemiological transition before the 1920s (column (6)). This estimation illustrates that the main effect of medical innovation – which captures the income level effect for countries in the earlier stage – is negative (-0.032) and comparable to that reported in column (3), while the interaction variable has a positive coefficient (0.071).[17] Conversely, when we interact medical innovation with a dummy identifying countries that transitioned from the 3^{rd} to the 4^{th} stage before the 1970s (column (7)), we get a pattern of results consistent with columns (4) and (5): the coefficient of the interaction term is negative and significant (-0.008), while the effects of the other regressors align with our baseline estimates. Overall, our findings support Hypothesis 2, indicating that medical innovations are associated with higher income levels only at intermediate values of longevity, i.e., between a minimum and a maximum threshold of life expectancy.

[16]The group of 4^{th} stage transition countries in 1970 includes Australia, Canada, Denmark, Japan, Netherlands, Norway, New Zealand, Sweden, Switzerland, and the UK. The group of 3^{rd} stage transition countries includes Austria, Belgium, Chile, Germany, Finland, France, Ireland, Italy, Mexico, and the US.

[17]As a robustness check, we also consider groups of countries in early stages of development and those beyond, based on life expectancy at 1914, so as to isolate the demographic impact of WWI, when three additional countries (Belgium, France, and the UK) had a life expectancy greater than 50 years. These estimates, which are available upon request, are similar to our baseline regressions.

Table 5: Income effects of medical innovation along the epidemiological transition

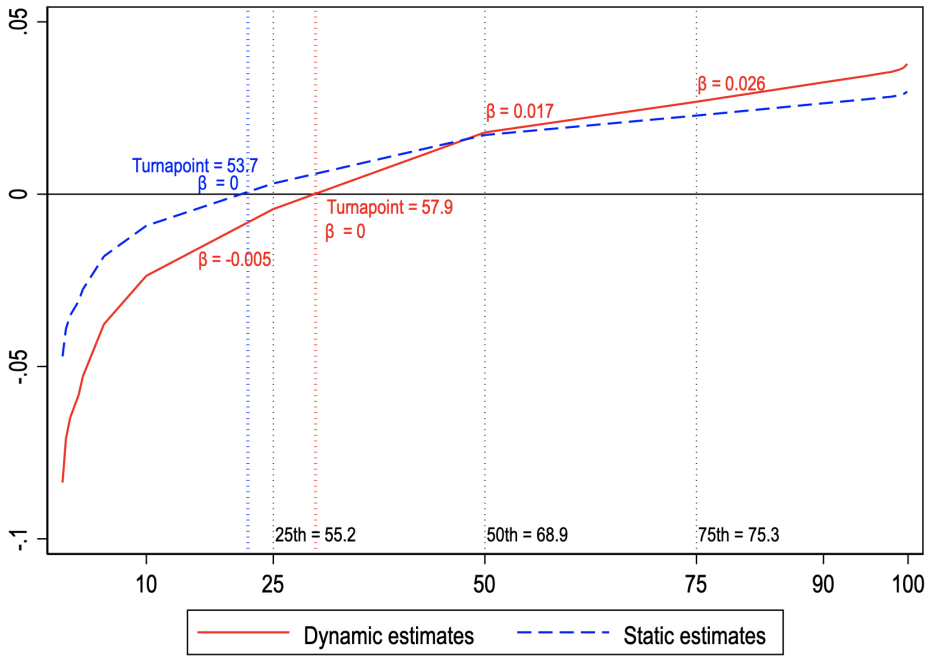
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dynamic regression (CS-ARDL)								Static regression (FE-CCE)
Medical innovation	0.004***	-0.014***	0.035***	0.014*	-0.066***	-0.032***	0.006***	-0.406***	-0.251***
	(0.001)	(0.003)	(0.004)	(0.008)	(0.007)	(0.003)	(0.002)	(0.031)	(0.090)
Industrial innovation	0.089***	0.093***	0.135***	0.100***	0.135***	0.120***	0.096***	0.086***	0.061***
	(0.004)	(0.006)	(0.006)	(0.014)	(0.009)	(0.005)	(0.004)	(0.004)	(0.011)
Longevity	1.600***	2.607***	2.594***	0.518	0.633	1.535***	1.329***	3.013***	1.438***
	(0.059)	(0.079)	(0.198)	(0.557)	(0.461)	(0.062)	(0.066)	(0.148)	(0.448)
Medical innov. × 3rd stage in 1920 (dummy)						0.071***			
						(0.003)			
Medical innov. × 4th stage in 1970 (dummy)							-0.008**		
							(0.003)		
Medical innovation × Longevity								0.100***	0.063***
								(0.008)	(0.022)
Speed of Adjustment	-0.133***	-0.112***	-0.171***	-0.269***	-0.310***	-0.137***	-0.165***	-0.212***	
	(0.017)	(0.026)	(0.022)	(0.051)	(0.037)	(0.017)	(0.019)	(0.019)	
Age threshold	None	<50 yrs before 1920	>50 yrs before 1920	<70 yrs before 1970	>70 yrs before 1970	None	None	None	None
Epidemiological transition		2nd stage	3rd stage	3rd stage	4th stage				
Time period of regression	1890-2018	1920-2018	1920-2018	1970-2018	1970-2018	1890-2018	1890-2018	1890-2018	1890-2018
Observations	2,286	1,001	846	470	470	2,286	2,286	2,286	2,486
R-squared	0.183	0.141	0.142	0.329	0.245	0.181	0.220	0.247	0.920
Countries	20	11	9	10	10	20	20	20	20

Notes: Dependent variable: GDP per capita. All variables are expressed in logs. Long-run estimates derived from a panel CS-ARDL regression with homogeneous parameters. Data span from 1890-2018. Estimates include country-specific fixed effects and common correlated effects. Newey-West standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Next, we aim to determine the timing at which the positive impact of medical innovation shows up, and examine how it varies with longevity by introducing an interaction between these two variables in column (8). By plotting the marginal effect of medical innovation along the distribution of longevity, we can then identify the timing at which the positive impact of medical innovation shows up. Admittedly, the results of this regression should be interpreted with caution because the variables have an integration order greater than one, which could potentially compromise the consistency of cointegration estimates. Following Eberhardt and Presbitero (2015), we circumvent this risk by running our model as a static regression (column (9)), finding elasticities that are generally in line with the long-run values presented in column (8) associated with the dynamic regression. As expected, the parameter estimates of the static model are smaller because they do not account for the dynamic adjustment in the effect of the explanatory variables.[18]

[18]Similar results emerge from the static regression augmented with the lagged values of CCE terms, used to filter out the dynamic response of the outcome variable to un-observable factors (results are unreported).

Figure 6: Income effect of medical innovation along longevity: within-country variation



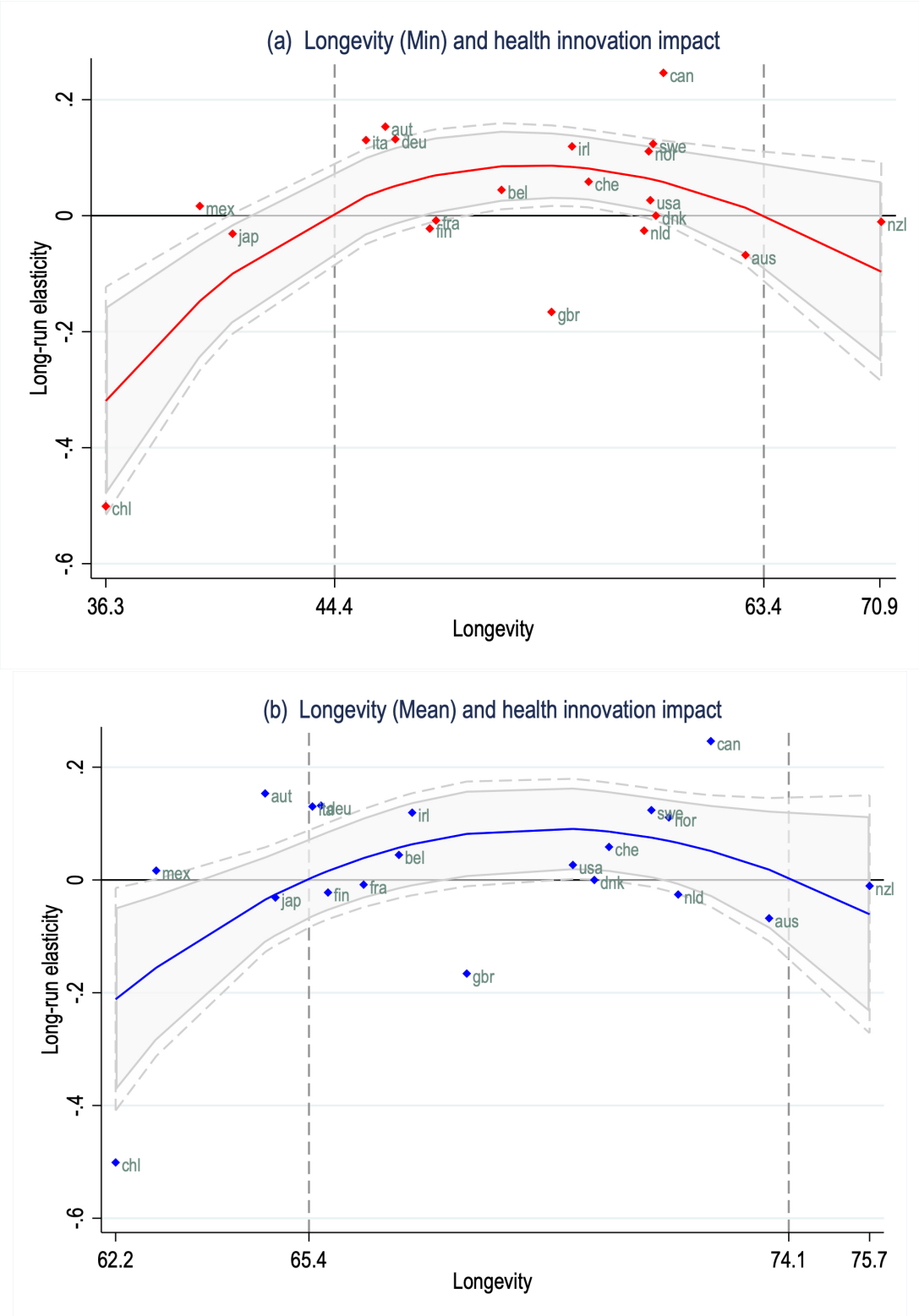
Notes: The graph plots homogeneous long-run estimates from cols. (5) and (6), Table 5.

Figure 6 illustrates the marginal effect of medical innovation along the distribution of life expectancy (by percentiles). The marginal effect is derived as $\partial y_{it}/\partial m_{it} = \hat{\beta}_m^T = \hat{\beta}_m + \hat{\beta}_{m,l} \cdot l_{it}$, where $\hat{\beta}_m$ and $\hat{\beta}_{m,l}$ are the parameters of medical innovation and of the interaction between this variable and longevity, respectively, as reported in Table 5. The solid red line uses parameters obtained from the dynamic regression (column 8), while the dashed blue line is based on static estimates (column (9)). Both distributions reveal that the marginal effect of medical innovation is negative at lower levels of longevity but increases quickly as life expectancy rises. The threshold at which the income effect of medical innovation becomes positive is between 54 and 58 years, which is close to the threshold (50 years) between the 2^{nd} and 3^{rd} stages of the epidemiological transition (see Omran, 1998). The figure also displays the value of life expectancy at the boundaries of each quartile of the distribution (55.2, 68.9, and 75.3 years, respectively), as well as the corresponding values of the marginal effect of medical innovation, $\hat{\beta}_m^T$ (-0.005, 0.017, and 0.026, respectively). Moving from the first to the second quartile of the longevity distribution, which corresponds to a 14-year increase in life expectancy (from 55 to 69 years), the total effect on income of medical innovation would surge from -0.005 to 0.017. However, a further inter-quartile move along the distribution, which is equal to a 6-year increase in life expectancy (from 69 to 75 years), would result in a more modest positive change in the income effect of medical innovation (from 0.017

to 0.026). This finding corroborates the second part of Hypothesis 2, namely that the positive income effect of medical innovation becomes weaker at higher levels of life expectancy and for later stages of the epidemiological transition.

Next, we aim to identify the non-linear impact of medical innovation on GDP per capita, which is driven by increases in life expectancy, by exploiting cross-country variation in the income effect of the former explanatory variable. Specifically, we estimate our dynamic regression model (CS-ARDL) country by country using the Mean Group regression and then illustrate in Figure 7 how the relationship between medical innovation and GDP per capita varies with each country's mean or minimum value of longevity over the sample period. Heterogeneous slope estimates of Eq. (1) are reported in Table B7 in Appendix B, and are by and large consistent with the results presented in Table 4. Our findings are thus robust to the issue of parameter heterogeneity. Based on such country-by-country estimates, we plot the distribution of income effects of medical innovations using both the average and minimum levels of longevity of our sample of countries. Life expectancy is lowest for all countries at the beginning of the sample period, implying that this value is predetermined with respect to medical innovation and hence is not affected by reverse causality. This implies that the plot using the minimum level of longevity is particularly suitable for inferring the shape of income effects along the distribution of longevity. The graph shows that, whether considering the minimum (panel (a)) or mean value (panel (b)) of life expectancy of each country, the marginal impact of medical innovation is hump-shaped along the longevity distribution. Medical innovation is found to exert a positive impact on GDP per capita only in countries where the minimum level of longevity is over 44 years, which is considerably lower than the threshold level we previously identified by exploiting within-country variation. If we consider the mean value of longevity, the initial threshold is less conservative and equals 64 years. Overall, Figure 7 provides strong evidence supporting the view that medical innovation has non-linear effects on GDP per capita, primarily through increases in longevity.

Figure 7: Income effect of medical innovation along longevity: cross-country variation



Notes: The graph plots country-specific long-run estimates, based on MG-CCE regression, of the income effect of medical innovation plotted against the minimum and the mean value of longevity (expressed in logs).

6 Conclusions

We analyze the effects of medical innovation and increasing life expectancy on economic growth. In so doing, we first propose a theoretical framework in which economic growth is driven by purposeful R&D investments in industrial innovation, while life expectancy is driven by increasing medical innovation and healthcare consumption per capita. In this setting, we show that medical innovation has the potential to raise economic growth, with an important transmission channel being the positive impact of medical innovation on life expectancy. Overall, the effect of medical innovation on economic growth is non-linear because in early stages of development (particularly in the 2^{nd} stage of the epidemiological transition according to the five-stage classification by Omran, 1998), health improvements mainly pertain to young cohorts before they reach working age. At the same time, the interest rate increases due to faster growth of aggregate demand. At this stage, economic growth could even decrease with medical innovation. In intermediate stages of development (i.e., the 3^{rd} stage of the epidemiological transition), workforce growth increases with medical innovation, and expanding life expectancy leads to higher investment. The latter effect puts downward pressure on the interest rate, which raises the incentives for R&D. At this stage, economic growth increases with medical innovation. In late stages of development (i.e., the 4^{th} stage of the epidemiological transition), expanding medical innovation has a lower impact on mortality and workforce growth but comes with an increasing demand for labor-intensive health care. As a consequence, medical innovation can reduce employment in industrial innovation, thus slowing down economic growth. Therefore, medical innovation will be growth-enhancing mainly for countries in intermediate stages of development, specifically the 3^{rd} stage of the epidemiological transition according to Omran (1998).

We test the theoretical predictions in the empirical section using historical data for industrialized countries and applying difference-in-differences local projection and a cointegration method of regression. Our empirical findings corroborate the causal effect of medical innovation on GDP per capita. Reassuringly, the quantitative effects are found to be very similar in both approaches. In addition, we find that the effect of medical innovation on economic growth is non-linear. We divide the sample into two groups based on the stage of the epidemiological transition. The first group consists of countries in the 2^{nd} stage of the transition, where increased longevity is linked to a growing population of young people. The second group includes countries that have progressed beyond this stage, where higher life expectancy leads to expansion in both the working age population and capital stock. We find that medical innovation only becomes beneficial after the 2^{nd} stage. However, we show that the positive effect of medical innovation on economic growth is strong only in the 3^{rd} stage of the epidemiological transition. Indeed, this effect levels off as life expectancy continues to rise, particularly as countries transition into the 4^{th} stage, when

resource-intensive medicine crowds out the rate of economic growth.

Why are these results important? First, our results suggest that investments in medical innovation raise economic growth only for countries in intermediate stages of development that have surpassed the 2^{nd} stage of the epidemiological transition but have not yet entered the 4^{th} stage. This could have implications for economic and health policies that take the growth effect of medical innovation into account but should, of course, not be understood as an indication against medical innovation if assessed on welfare grounds (Kuhn and Prettner, 2016; Jones, 2016; Frankovic and Kuhn, 2023). Second, where medical innovation is beneficial for economic growth in intermediate stages of development, the crucial transmission channel operates through rising life expectancy (with all the positive repercussions on individual and social well-being). Third, there are spillover effects between medical innovation and industrial innovation such that the long-run dynamic benefits that arise from investments in medical innovation are greater than what static cost-benefit considerations would suggest.

For future research, the following avenues seem promising: i) While, for analyzing the research questions in our setting, we do not need an endogenous utilization of health care in the theoretical model, endogenizing health care and exploring in greater detail its role in the innovation – longevity – growth nexus represents a significant advance. ii) Similarly, endogenizing the process of medical progress should provide additional understanding, especially of the allocation of R&D resources. iii) Exploring the role of institutions, such as the nature of the health care system, and the scope for accompanying policies, such as more flexible retirement policies allowing people to work to higher ages, in shaping and possibly enhancing the growth effect of medical innovations. iv) Considering the role of radical versus incremental innovations may help to understand whether decreasing returns to innovation are a result of a long-lasting lack of breakthroughs.

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A Derivations

A.1 Population size

We get the population size at time t by integrating over the dates of birth for all cohorts that are alive, namely

$$N(t) = \int_{-\infty}^{t} N(v,t)\mathrm{d}v = \int_{-\infty}^{t} N(0)e^{nv}\beta e^{-\mu(t-v)}\mathrm{d}v = N(0)\beta e^{-\mu t}\int_{-\infty}^{t} e^{(n+\mu)v}\mathrm{d}v =$$
$$= N(0)\beta\frac{e^{-\mu t}e^{(n+\mu)t}}{\beta} = N(0)e^{nt}. \tag{A.1}$$

A.2 The individual Euler equation

The current-value Hamiltonian is

$$H = \log(c) + \lambda\left[(r+\mu)a + w(1-h) - c\right].$$

The first-order conditions are

$$\frac{1}{c} = \lambda, \tag{A.2}$$
$$\dot{\lambda} = (\rho - r)\lambda. \tag{A.3}$$

Taking the time derivative of Eq. (A.2) and plugging it into Eq. (A.3) yields

$$\frac{\dot{c}}{c} = r - \rho,$$

which is the familiar individual Euler equation.

A.3 Aggregation

Differentiating aggregate wealth with respect to time, we get

$$\dot{\Omega}(t) = -\mu\Omega(t) + e^{-\mu t}\beta N(0)a(t,t)e^{\beta t} + e^{\mu t}\beta N(0)\int_{-\infty}^{t}\dot{a}(t_0,t)e^{\beta t_0}dt_0$$
$$= -\mu\Omega(t) + e^{\mu t}\beta N(0)\int_{-\infty}^{t}\dot{a}(t_0,t)e^{\beta t_0}dt_0,$$

where the second equality uses the fact that $a(t,t) = 0$. Using the flow budget constraint (2), it follows that:

$$\dot{\Omega}(t) = -\mu\Omega(t) + e^{-\mu t}\beta N(0)\int_{-\infty}^{t}(r+\mu)a(t_0,t)e^{\beta t_0}dt_0 + e^{-\mu t}N(0)w(t)[1-h(t)]e^{\beta t}$$
$$- e^{-\mu t}\beta N(0)\int_{-\infty}^{t}c(t_0,t)e^{\beta t_0}dt_0 = r\Omega(t) + w(t)[1-h(t)]N(0)e^{nt} - C(t)$$
$$= r\Omega(t) + w(t)[1-h(t)]N(t) - C(t),$$

which is the aggregate law of motion for assets. Differentiating aggregate consumption with respect to time, we get

$$\begin{aligned}\dot{C}(t) &= -\mu C(t) + e^{-\mu t}\beta N(0)c(t,t)e^{\beta t} + e^{-\mu t}\beta N(0)\int_{-\infty}^{t}\dot{c}(t_0,t)e^{\beta t_0}dt_0 \\ &= -\mu C(t) + \beta N(0)e^{nt}c(t,t) + e^{-\mu t}\beta N(0)\int_{-\infty}^{t}\dot{c}(t_0,t)e^{\beta t_0}dt_0 \\ &= -\mu C(t) + \beta N(t)c(t,t) + e^{-\mu t}\beta N(0)\int_{-\infty}^{t}\dot{c}(t_0,t)e^{\beta t_0}dt_0.\end{aligned}$$

Reformulating an agent's optimization problem subject to its lifetime budget restriction, stating that the present value of lifetime consumption expenditures has to be equal to the present value of lifetime non-interest income plus initial assets, yields the optimization problem:

$$\begin{aligned}\max_{c(t_0,v)} \quad U \quad &= \int_t^{\infty} e^{(\rho+\mu)(t-v)}\log(c(t_0,v))\mathrm{d}v \\ s.t. \qquad & a(t_0,t) + \int_t^{\infty} w(v)\left[1-h(v)\right]e^{-R(t,v)}\mathrm{d}v = \int_t^{\infty} c(t_0,v)e^{-R(t,v)}\mathrm{d}v,\end{aligned}$$

where $R(t,v) = \int_t^v \left[r(s)+\mu\right]\mathrm{d}s$. The first-order condition for optimal consumption is

$$\frac{e^{(\rho+\mu)(t-v)}}{c(t_0,v)} = \lambda(t)e^{-R(t,v)}.$$

In period $v = t$, the previous equation becomes $1/c(t_0,t) = \lambda(t)$. Therefore, we can write

$$\begin{aligned}\frac{e^{(\rho+\mu)(t-v)}}{c(t_0,v)} &= \frac{e^{-R(t,v)}}{c(t_0,t)}, \\ c(t_0,t)e^{(\rho+\mu)(t-v)} &= c(t_0,v)e^{-R(t,v)}.\end{aligned}$$

Integrating the previous equation, we get

$$\begin{aligned}\int_t^{\infty} c(t_0,t)e^{(\rho+\mu)(t-v)}\mathrm{d}v &= \int_t^{\infty} c(t_0,v)e^{-R(t,v)}\mathrm{d}v \\ \Leftrightarrow \frac{c(t_0,t)}{\rho+\mu} &= a(t_0,t) + \int_t^{\infty} w(v)\left[1-h(v)\right]e^{-R(t,v)}\mathrm{d}v \\ \Leftrightarrow \frac{c(t_0,t)}{\rho+\mu} &= a(t_0,t) + \Lambda(t),\end{aligned}$$

where $\Lambda(t)$ refers to human wealth that does not depend on the date of birth. The previous derivations imply that individuals consume a constant fraction of their total wealth at each point in time, that is

$$c(t_0,t) = (\rho+\mu)[a(t_0,t)+\Lambda(t)], \tag{A.4}$$

where the marginal propensity to consume out of total wealth is given by the "effective" discount rate $\rho + \mu$. Using Eq. (A.4) and integrating yields aggregate consumption

$$\begin{aligned} C(t) &= \int_{-\infty}^{t} c(t_0, t) N(t_0, t) dt = e^{-\mu t} b N(0) \int_{-\infty}^{t} c(t_0, t) e^{bt} dt_0 \\ &= e^{-\mu t} \beta N(0)(\rho + \mu) \left[\int_{-\infty}^{t} a(t_0, t) e^{\beta t} dt_0 + \frac{e^{\beta t}}{\beta} \Lambda(t) \right] \\ &= (\rho + \mu)\Omega(t) + (\rho + \mu) N(t) \Lambda(t). \end{aligned}$$

Since newborns do not own any financial assets, their consumption follows directly from Eq. (A.4) as

$$c(t, t) = (\rho + \mu)\Lambda(t).$$

Now, we take the derivative of aggregate consumption with respect to time, that is

$$\begin{aligned} \dot{C}(t) &= -\mu \left[(\rho + \mu)\Omega(t) + (\rho + \mu) N(t) \Lambda(t) \right] \\ &\quad + \beta N(t)(\rho + \mu)\Lambda(t) + e^{-\mu \cdot t} \beta N(0) \int_{-\infty}^{t} c(t_0, t) e^{\beta t_0} (r - \rho) \mathrm{d}t_0 \\ &= -\mu(\rho + \mu)\Omega(t) + (\rho + \mu) N(t) \Lambda(t)(\beta - \mu) + C(t)(r - \rho) \\ &= -\mu(\rho + \mu)\Omega(t) + \mu(\rho + \mu) N(t) \Lambda(t) C(t)(r - \rho). \end{aligned}$$

Thus, we get

$$\begin{aligned} \frac{\dot{C}(t)}{C(t)} &= (r - \rho) - \mu(\rho + \mu)\frac{\Omega(t)}{C(t)} + \mu(\rho + \mu)\frac{N(t)\Lambda(t)}{C(t)} \\ &= (r - \rho) - \mu(\rho + \mu)\frac{\Omega(t)}{C(t)} + \mu\frac{[C(t) - (\rho + \mu)\Omega(t)]}{C(t)} \\ &= r - \rho + \mu - (n + \mu)(\rho + \mu)\frac{\Omega(t)}{C(t)}. \end{aligned}$$

Finally, we rewrite the expressions for the law of motion of aggregate assets and the aggregate Euler equation

$$\dot{\Omega}(t) = r\Omega(t) + w(t)[1 - h(t)]N(t) - C(t), \tag{A.5}$$

$$\frac{\dot{C}(t)}{C(t)} = r - \rho + \mu - (n + \mu)(\rho + \mu)\frac{\Omega(t)}{C(t)}. \tag{A.6}$$

A.4 Expressing the interest rate in terms of output and capital

We can rewrite $r(t)$ as

$$r(t) = \alpha p(t) = \alpha^2 L_Y(t)^{1-\alpha} x(t)^{\alpha - 1} = \alpha^2 L_Y(t)\frac{x(t)^{\alpha}}{x(t)} = \alpha^2 L_Y(t)\frac{A(t)x(t)^{\alpha}}{A(t)x(t)} = \alpha^2 \frac{Y(t)}{K(t)}.$$

A.5 Expressing output in terms of aggregate capital

We can rewrite $Y(t)$ as

$$Y(t) = L_Y(t)^{1-\alpha}A(t)x(t)^{\alpha} = L_Y(t)^{1-\alpha}A(t)\left(\frac{K(t)}{A(t)}\right)^{\alpha} = [A(t)L_Y(t)]^{1-\alpha}K(t)^{\alpha}.$$

A.6 Calculating the ratio wN/Ω

Since the free-entry condition in the R&D sector implies that $w(t) = V_A(t)\nu A(t)/N(t)$ and aggregate assets amount to $\Omega(t) = K(t) + V_A(t)A(t)$, we can express the ratio $w(t)N(t)/\Omega(t)$ as

$$\frac{w(t)N(t)}{\Omega(t)} = \frac{V_A(t)\nu A(t)}{K(t) + V_A(t)A(t)} = \frac{V_A(t)\nu\frac{A(t)}{Y(t)}}{\frac{K(t)}{Y(t)} + V_A(t)\frac{A(t)}{Y(t)}} = \frac{r(t)\nu(1-\alpha)}{r(t) - \alpha n},$$

where the last equality of this equation follows from

$$V_A(t) = \frac{\alpha(1-\alpha)Y(t)/A(t)}{r - n}$$

and $K(t)/Y(t) = \alpha^2/r(t)$.

A.7 The r_d locus

The r_d locus is obtained by setting Eq. (5) equal to Eq. (6). Denoting the ratio C/Ω as ξ, we can express the interest rate as a function of ξ, μ, and h, that is

$$r = \frac{\alpha\left[(1-h)\nu\xi + \mu^2 + \rho(\mu+\xi)\right] + n\left[\alpha(\mu+\rho) + \xi\right]}{(\alpha+1)\xi}.$$

Since the partial derivative of r with respect to ξ is negative, the r_d locus is a downward-sloping relationship between r and C/Ω. The effects of increased ν, μ, n, and h can be calculated through simple comparative statics. The partial derivatives of r with respect to ν, μ and n are positive, whereas the one with respect to h is negative. Therefore, this equilibrium locus shifts up if either research productivity, ν, the mortality rate, μ, or the population growth rate, n, increases, and down if the per capita level of medical treatment, h, increases.

A.8 The r_u locus

The r_u locus is obtained by setting Eq. (5) equal to Eq. (7) and solving for r, that is

$$r = \frac{n(1+\alpha)^2 + \alpha[\alpha\nu(1-h) + \xi] + \sqrt{\alpha^2[\xi + \alpha\nu(1-h)]^2 + 2\alpha n\left(1-\alpha^2\right)\left[\xi - \alpha\nu(1-h)\right] + n^2\left(1-\alpha^2\right)^2}}{2(1+\alpha)}.$$

Since the partial derivative of r with respect to ξ is positive, the r_u locus is an upward-sloping relationship between r and C/Ω. As can be easily ascertained, this equilibrium locus does not depend on the mortality rate, μ. The partial derivatives of r with respect to ν and n are positive, while the derivative with respect to h is negative. Therefore, this equilibrium locus shifts up if either research productivity, ν, the population growth rate, n, increases, or if the per capita level of healthcare, h, decreases.

B Empirical appendix

B.1 Summary statistics

In this section, we provide descriptive statistics for the entire sample and by country.

Table B1: Summary statistics for the total sample (1890-2018)

	Mean	SD	Min	Max
Income per capita	20,222	15,891	1,965	85,183
Medical patent stock p.c.	11.2	27.5	0.0	261.2
Industrial patent stock p.c.	181.9	317.2	0.0	1860.6
Life expectancy	66.4	12.3	25.8	84.5

Table B2: Summary statistics by country (1890-2018)

	Income per capita			Medical patent stock per capita			Industrial patent stock per capita			Life expectancy		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Australia	20,719	6,731	49,654	5.1	0.0	33.0	45.8	0.6	244.8	69.4	53.0	83.3
Austria	18,958	3,539	51,304	3.2	0.0	21.3	59.8	0.2	261.0	63.0	37.3	81.4
Belgium	17,217	3,008	44,334	4.4	0.0	32.4	67.2	1.6	248.7	64.8	43.1	81.5
Canada	20,228	4,350	47,909	7.1	0.1	35.6	135.4	38.6	449.1	66.7	45.2	82.3
Chile	7,531	2,124	24,329	0.2	0.0	2.5	1.5	0.1	4.6	55.1	29.0	80.0
Germany	19,408	4,358	50,759	9.2	0.1	47.2	203.5	9.3	744.0	64.7	40.5	81.2
Denmark	20,354	4,596	49,899	15.3	0.0	106.5	90.3	1.8	427.8	67.6	46.8	80.8
Finland	15,487	2,213	44,851	6.3	0.0	44.1	175.4	0.2	1186.2	62.9	32.8	81.7
France	16,999	3,941	42,833	7.3	0.0	36.3	102.8	0.9	344.8	64.1	34.8	82.5
Ireland	18,357	3,521	85,183	9.1	0.0	69.2	40.2	1.5	367.7	66.8	49.4	82.1
Italy	16,470	3,314	41,783	2.1	0.0	10.1	32.3	0.2	126.5	62.7	25.8	83.4
Japan	14,784	1,664	43,340	8.6	0.0	47.2	328.9	0.0	1860.6	60.0	30.5	84.5
Mexico	9,007	2,821	19,655	0.1	0.0	0.6	1.6	0.5	5.3	51.8	23.3	75.3
Netherlands	21,102	5,229	53,901	8.0	0.0	56.4	136.2	0.8	725.4	67.8	43.9	82.1
Norway	26,218	4,290	71,917	5.4	0.0	33.7	62.6	1.0	255.8	68.9	48.6	82.3
New Zealand	18,123	6,505	40,230	3.9	0.1	25.1	29.6	3.9	110.9	74.8	68.8	82.1
Switzerland	32,757	7,784	70,923	38.2	0.2	261.2	476.2	16.0	1292.4	67.1	44.7	83.6
Sweden	18,022	3,024	47,844	20.8	0.0	118.4	260.3	5.1	1007.0	69.0	49.8	82.7
UK	17,410	5,594	43,181	5.2	0.1	23.2	109.1	10.6	236.8	65.8	44.1	81.2
USA	22,950	4,513	59,849	40.7	3.6	179.9	908.1	279.3	1832.7	65.6	45.2	78.9

B.2 Additional results

In this section, we provide a number of robustness checks and extensions of our primary analysis.

Table B3: Medical innovation and income levels (1890-2018): long-run estimates with controls (CS-ARDL)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Medical innovation	0.004***	0.014***	0.008***	0.019***	0.005**	0.005**	0.006***	0.005***	0.005***	0.003*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Industrial innovation	0.089***	0.096***	0.110***	0.054***	0.048***	0.064***	0.096***	0.100***	0.097***	0.092***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Longevity	1.600***	1.105***	1.070***	0.257***	1.868***	1.462***	1.557***	1.478***	1.545***	1.611***
	(0.058)	(0.065)	(0.066)	(0.075)	(0.047)	(0.061)	(0.059)	(0.060)	(0.059)	(0.059)
Capital stock p.w.		0.059***								
		(0.021)								
Human capital index			0.124***							
			(0.040)							
Public debt/GDP				0.074***						
				(0.004)						
Private credit/GDP					-0.282***					
					(0.008)					
Export/GDP						0.338***				
						(0.009)				
Medical innovation spillovers										
population-weighted inverse-distance							0.142***			
							(0.008)			
squared population-weighted inverse-distance								0.138***		
								(0.006)		
inverse-distance									0.143***	
									(0.008)	
Industrial innovation										
population-weighted inverse-distance										-0.049***
										(0.012)
Speed of adjustment	-0.133***	-0.175***	-0.184***	-0.101***	-0.123***	-0.149***	-0.139***	-0.143***	-0.139***	-0.133***
	(0.017)	(0.025)	(0.020)	(0.015)	(0.014)	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)
Obs.	2,286	2,286	2,286	1,624	1,664	1,692	2,286	2,286	2,286	2,286
R-squared	0.183	0.220	0.233	0.163	0.190	0.203	0.182	0.181	0.181	0.182
Countries	20	20	20	16	16	16	20	20	20	20

Notes: Long-run estimates derived from a panel CS-ARDL regression with homogeneous parameters. Data span from 1890-2018. All variables are expressed in logs. Estimates include country-specific fixed effects and common correlated effects. Newey-West standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B4: Medical innovation and income levels (1981-2018): long-run estimates with controls (CS-ARDL)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medical innovation	0.015***	0.195***	0.097***	0.018***			-0.003	0.108***
	(0.003)	(0.006)	(0.004)	(0.003)			(0.003)	(0.004)
Longevity					3.295***		3.083***	9.261***
					(0.359)		(0.584)	(0.625)
Industrial innovation						0.033***	0.047***	0.010
						(0.009)	(0.015)	(0.010)
Total medical exp./GDP								-0.747***
								(0.029)
Speed of adjustment	-0.197***	-0.159***	-0.140***	-0.181***	-0.185***	-0.206***	-0.406***	-0.097***
	(0.032)	(0.041)	(0.043)	(0.030)	(0.025)	(0.032)	(0.051)	(0.037)
Innovation indicator	Patents	Patents	Patents	R&D	Patents	Patents	Patents	Patents
Source	USPTO	EPO	PCT	OECD	USPTO	USPTO	USPTO	USPTO
Obs.	700	700	700	700	700	700	720	720
R-squared	0.227	0.153	0.205	0.239	0.218	0.237	0.349	0.205
Number of groups	20	20	20	20	20	20	20	20

Notes: Long-run estimates derived from a panel CS-ARDL regression with homogeneous parameters. Data span from 1981-2018. All innovation variables are expressed as per capita stocks. All variables are expressed in logs. Estimates include country-specific fixed effects and common correlated effects. Newey-West standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B5: Medical innovation and income levels (1890-2018): static estimates based on non-overlapping five-year intervals

	(1)	(2)	(3)	(4)	(5)	(6)
Medical innovation	0.259***			0.142***	0.113***	
	(0.011)			(0.008)	(0.010)	
Medical equip.		0.165***				0.043***
		(0.023)				(0.008)
Drugs		0.069***				0.061***
		(0.018)				(0.006)
Longevity			3.384***	2.345***	1.944***	2.113***
			(0.146)	(0.122)	(0.134)	(0.124)
Industrial innovation					0.098***	0.094***
					(0.019)	(0.018)
Obs.	540	540	518	518	518	518
R-squared	0.384	0.496	0.235	0.125	0.117	0.103

Notes: Estimates derived from a panel static regression with homogeneous parameters. Data span from 1890-2018. All innovation variables are expressed as per capita stocks. All variables are expressed in logs. Estimates include country-specific fixed effects and common correlated effects. Newey-West standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B6: Medical innovation and income levels (1890-2018): dynamic estimates based on non-overlapping five-year intervals

	(1)	(2)	(3)	(4)	(5)	(6)
Medical innovation	0.243***			0.127***	0.108***	
	(0.022)			(0.015)	(0.016)	
Medical equip.		0.107***				0.044***
		(0.035)				(0.014)
Drugs		0.103***				0.054***
		(0.021)				(0.009)
Longevity			3.401***	2.411***	2.187***	2.128***
			(0.270)	(0.197)	(0.242)	(0.201)
Industrial innovation					0.061*	0.080**
					(0.037)	(0.031)
Speed of adjustment	-0.920***	-0.941***	-1.193***	-1.033***	-1.021***	-0.972***
	(0.054)	(0.053)	(0.054)	(0.059)	(0.057)	(0.055)
Obs.	500	500	455	450	450	450
R-squared	0.391	0.505	0.233	0.120	0.103	0.096

Notes: Long-run estimates derived from a panel dynamic ARDL(1,1) regression with homogeneous parameters. Data span from 1890-2018. All innovation variables are expressed as per capita stocks. All variables are expressed in logs. Estimates include country-specific fixed effects and common correlated effects. Newey-West standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B7: Medical innovation and income levels: long-run estimates with heterogeneous (country-by-country) parameters (CS-ARDL, Mean Group regression)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Simple mean				Robust mean			
Medical innovation	0.039***			0.003	0.037***			0.021***
	(0.011)			(0.029)	(0.012)			(0.009)
Industrial innovation		0.084**		0.112**		0.073*		0.083*
		(0.038)		(0.048)		(0.040)		(0.040)
Longevity			0.560**	0.813**			0.558**	0.806**
			(0.260)	(0.341)			(0.280)	(0.375)
MRSE	0.103	0.099	0.094	0.065	0.103	0.099	0.094	0.065
Obs.	2,480	2,480	2,480	2,480	2,480	2,480	2,480	2,480

Notes: Long-run estimates derived from a panel CS-ARDL regression with heterogeneous parameters. Data span from 1890-2018. All variables are expressed in logs. Estimates include country-specific fixed effects and common correlated effects. Columns (1)-(3) report the simple mean of country-specific coefficients. Columns (4)-(6) report the robust regression mean of country-specific coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.3 Unit roots, Weak causality and Cross-sectional Dependence testing

Table B8: Unit root testing (Pesaran et al., 2013)

	Income per capita	Medical innovation	General innovation	Longevity
Simple mean	-2.12	-2.64(*)	-2.60	-2.29
Robust mean	-2.11	-2.64(*)	-2.07	-2.26
Critical values		1%	5%	10%
t=100		-2.84	-2.65	-2.54
t=200		-2.98	-2.78	-2.69

Notes: The table reports the unit root test robust to cross-sectional dependence induced by multiple un-observable factors (Pesaran et al., 2013). Critical Values. (a) $t = 100$ 1%: -2.97; 5%: -2.77; 10%: -2.65. (b) $t = 200$. 1%: -3.16; 5%: -2.94; 10%: -2.86.

To assess the direction of causality among the variables of our (long-run) cointegration relationship (Eq. 11), we perform a battery of weak causality tests. We estimate one equation with an Error Correction Mechanism (ECM) representation for each potentially endogenous variable ($z = y, x$), including the error correction (disequilibrium) term of Eq. (11) as well as the first differences (and their lags, denoted by p) of the variables in the vector z:

$$\Delta y_{it} = d_y \, \hat{\varepsilon}_{it-1} + \sum_{p=1}^{P} \eta_{yp} \Delta y_{it-p} + \sum_{p=1}^{P} \eta_{xp} \Delta x_{it-p} + \alpha_{y,i} + \lambda_{y,i} f_{yt} + \epsilon_{y,it},$$

$$\Delta x_{it} = d_x \, \hat{\varepsilon}_{it-1} + \sum_{p=1}^{P} \eta_{xp} \Delta x_{it-p} + \sum_{p=1}^{P} \eta_{yp} \Delta y_{it-p} + \alpha_{x,i} + \lambda_{x,i} f_{xt} + \epsilon_{x,it},$$

where $\hat{\varepsilon}_{it} = y_{it} - \hat{\beta}_i - \hat{\beta}_1 x_{it} - \hat{\lambda}_i \, f_t$. Based on the Granger Representation Theorem, if $d_y < 0$ and $d_x = 0$, causality runs from x to y, whereas it runs in the other direction if $d_y = 0$ and $d_x < 0$. The table indicates that GDP per capita is endogenous to the other variables of the model, whilst evidence for industrial innovation remains somewhat ambiguous.

Table B9: Cointegration and Weak exogeneity testing

	Income p.c.	Medical innovation	Industrial innovation	Longevity
1 lag	-0.106***	0.076	0.101***	0.009
	(0.017)	(0.114)	(0.031)	(0.006)
3 lags	-0.125***	0.142	0.050*	0.002
	(0.017)	(0.128)	(0.030)	(0.006)

Notes: The table reports the test for weak exogeneity in the long-run errors derived from estimates in col. (5), Table 4. The coefficients refer to the disequilibrium term ($\hat{\varepsilon}_{it}$) entering the regression having the variable reported by column as dependent variable. Regressions by rows use one- and three-year lags of first differenced variables and common correlated effects, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B10: Cross-sectional dependence testing (1920-2019)

	(1)	(2)	(3)	(4)	(5)	(6)
CD test statistic	-6.52***	-6.64***	-6.28***	-4.05***	-4.43***	-4.48***
P-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Notes: The table reports the value of the CD statistic test (Pesaran, 2015) on the residuals of the regressions in Table 4. H0: panel units are cross-sectional dependent. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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