International Medical R&D Spillovers*

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Abstract

Does medical technology originating in countries close to the technology frontier have a significant impact on health outcomes in countries distant from this frontier? This paper considers a framework where lagging countries may benefit from medical technology (a result of research and development by countries close to the frontier) that is embodied in medical imports or diffuses in the form of ideas. Using a novel dataset from a cross-section of 73 technology-importing countries, we show that medical technology diffusion is an important contributor to improved health status, as measured by life expectancy and mortality rates.

Keywords: Health status, medical technology diffusion, R&D spillovers.

JEL Classification: O30, O40

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1 Introduction

One of the most fundamental aspects of economic development and a nation's welfare is the population's level of health as manifested by a variety of indicators, such as life expectancy at birth or mortality rates. Along with the level of education, health is a basic component of a nation's human capital. Understanding the main forces that have led to improvements in life expectancy is one of the fundamental questions of economic policy. A number of commentators have pointed out that improvements in life expectancy over the past two centuries have been driven primarily by two forces: general increases in the level of per capita income and the diffusion of medical technology from countries at the core of medical innovation to the periphery. While income is primarily thought to be responsible for health improvements in the 19th century, the diffusion of medical technology is thought to have been responsible during the 20th century, especially the latter half of the century. For instance, Kremer (2002, p. 67) emphasizes the importance of modern medical technologies in allowing "... tremendous improvements in health even at low income levels."[1] Moreover, commentators have pointed out that while income inequality has tended to increase throughout the past two centuries, inequality in life expectancy has tended to decline, especially during the past fifty years or so. Bourguignon and Morrisson (2002, p. 741) report that "... unlike income, world inequality in life expectancy fell considerably after 1930, as improvement in world mean life expectancy accelerated."[2] Becker, Philipson and Soares (2003, p.1) argue that "...in the last 50 years, countries starting with modest longevity levels experienced life expectancy gains significantly larger than countries starting with high longevity levels." Fogel (1994, p. 388) points to a potential explanation for the acceleration of life expectancy improvements in "... the huge social investments made between 1870 and 1930, whose payoffs were not counted as part of national income during the 1920's and 1930's even though they produced a large stream of benefits during these decades" and adds that he "... refer[s], of course, to the social investment in biomedical research."

The general trends in life expectancy over the past two centuries are shown in Table 1. The table shows the inexorable increase, across the globe, in life expectancy since 1820, punctuated by

[1] He offers an illuminating observation on the importance of technology diffusion in boosting life expectancy in the case of Vietnam where at the end of the 20th century life expectancy stood at "... 69 years despite a per capita income that according to official statistics is less than one-tenth that of the United States in 1900, which had a 47-year life expectancy."

[2] In related work, Jamison, Sandbu, and Wang (2001) document the importance of different rates of technological progress across countries for the declining cross-country variation in infant mortality rates.

Table 1: Life Expectancy at Birth: 1820-2000

Region	**1820**	**1890**	**1910**	**1929**	**1950**	**1960**	**1970**	**1980**	**1990**	**2000**
Sub Saharan Afr	25.3	25.6	26.7	30.6	36.3	40.2	44.2	47.6	50.0	46.5
Latin America	29.1	33.2	37.2	41.8	51.7	56.4	60.5	64.6	67.9	70.4
East Asia	25.1	25.2	26.2	30.2	43.5	39.2	59.1	64.4	67.3	69.1
South Asia	23.0	23.0	23.0	27.0	40.6	43.9	48.9	53.7	58.7	62.7
High Income	34.6	42.5	48.7	56.8	65.8	69.6	71.4	74.0	76.1	78.0
World	26.5	29.6	32.4	37.6	48.8	50.2	58.6	62.6	65.3	66.5

Notes: Each regional average is population weighted. Country data for 1820-1950 are from Bourguignon and Morrisson (2002) and for 1960-2000 from the World Development Indicators (2002). South Asia includes Bangladesh, India and Pakistan. High Income includes Australia, Austria, Belgium, Canada, Czechoslovakia, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom and the United States. The other three regions are as defined by the World Bank.

two periods of falling life expectancy: East Asia during the 1950s and Sub-Saharan Africa during the last decade of the 20th century.[3] What is evident is that throughout the 19th century, except for Latin America,[4] the countries of the periphery experienced hardly any improvements in life expectancy, while the high income economies experienced a 40 percent increase from 35 years in 1820 to 49 in 1910. More importantly, the life expectancy gap between the high-income economies and the rest of the world widened during the 19th century: the gap between Sub-Saharan Africa and Asia, on the one hand, and the high-income economies increased from about 9 years in 1820 to more than 20 years in 1910. The first half of the 20th century witnessed the first important increases in life expectancy in the developing world: between 1910 and 1950 life expectancy increased by 36 percent in Sub-Saharan Africa, by 39 percent in Latin America, by 66 percent in East Asia and by 76 percent in South Asia. Life expectancy improvements accelerated in the developing world during the second half of the 20th century: over the 1950-2000 period life expectancy increased by 3.7 years per decade in Latin America, by 6 years in East Asia, by 4.5 in South Asia, and by 3.4 years in Sub-Saharan Africa (until 1990 and the reversal during 1990-2000.) The corresponding

[3]The drop in life expectancy in East Asia in the 1950s is wholly explained by the reduction in China's life expectancy from 44 years in 1950 to 36 years in 1960. This coincided with the policies adopted by the victorious Chinese Communist Party following the civil war of the late 1940s culminating in the Great Leap Forward and the great famine of the late 1950s. Sub-Saharan's recent reduction in life expectancy is due to the rapid spread of HIV/AIDS across the continent.

[4]Our Latin America grouping in Table 1 includes what were some of the wealthiest countries of the 19th century (e.g. Argentina and Chile). Bourguignon and Morrisson (2002) chose to include these countries in a separate category: Western Europe and European offshoots. In Table 1 we adopt the World Bank classification of country groupings to reflect our empirical emphasis on the recent experience of various countries.

figure for the high-income economies was 2.5 years per decade.[5]

In this paper, we argue that research and development (R&D)-induced advances in medical technology systematically diffuse across the world and are, thus, partly responsible for the decline in life expectancy inequality discussed above. We focus on the diffusion of medical technology both in terms of its embodiment in medicines and medical equipment that are exported from the innovating countries to the rest of the world (and thus can be termed as the 'indirect' benefits of R&D-induced medical technology) and the diffusion of ideas arising from R&D in advanced countries (and can, thus, be termed as the 'direct spillover' benefits of medical technology.) The importance of the diffusion of medical technology in improving health outcomes across the world is well known to social scientists and epidemiologists but has received little attention by economists.

In a fascinating book, Rocco (2004) traces the importance of medical discoveries and their diffusion across the globe in controlling the spread of malaria and, thus, facilitating major global economic events.[6] The property of the bark of the cinchona tree, native to the Peruvian Andes, to cure the symptoms of malaria was first noted by Jesuit priests (sent to set up missions in South America) in the College of San Pablo in Lima in the first half of the 17th century. Knowledge of the miraculous qualities of the cinchona bark spread to Europe, with Peru serving as a center for the distribution and trade in the bark. By the late 18th century, trade in cinchona bark accounted for a large part of transatlantic trade and "official imports of cinchona ... amounted to a total that was valued at more than ten million *reales* ... three times that of exotic hardwoods from the Indies, and ... nearly 2 per cent of all imports from South America" (p. 83). It was not until the last decade of the 19th century that the role played by the *anopheles* mosquito in the transmission of the *Plasmodium* malaria parasites to human beings became known through the research of Major Ronald Ross in India. Soon knowledge of his breakthrough was transmitted to England and the rest of the scientific community through his correspondence with Patrick Manson, a specialist in tropical medicine. Both trade in commodities and ideas played the decisive part in combating the devastating effects of this disease.

Our paper concentrates on the channels by which medical technology diffuses from a handful

[5]Bourguignon and Morrisson (2002) calculate that the Theil index of life expectancy inequality rose throughout the 19th century to reach 0.045 by 1910 and then declined through most of the 20th century to reach 0.013 by 1992.

[6]These included, among others: (a) the opening up of west and central Africa to exploration and eventual colonization; (b) the unsuccessful attempt by the French to construct the Panama canal, due to their inability to control malaria, and the success of American engineers in this endeavor, after controlling the spread of the disease; and (c) the opening up of the American west.

of countries to the rest of the world and its impact on health. We argue that countries benefit from foreign medical R&D even in the absence of domestic medical R&D, and the extent of these beneficial effects is transmitted through two channels. First, imports of medical goods. Similar to Caselli and Wilson (2003) and as shown by Eaton and Kortum (2001) for capital equipment, we consider that production of goods embodying medical technology is concentrated in a small number of R&D-intensive countries while the rest of the world typically imports these goods; thus, these imports capture adequately the impact of new embodied medical technology on the overall health level in these countries. Second, R&D carried out in advanced economies may also have spillover effects in terms of generating knowledge and ideas that can be used (as in the case of capital goods) by producers other than those carrying out the R&D. These producers may be located within or across the country's borders. This should be particularly important in the case of providers of medical services (say physicians) who are likely to improve their practice by utilizing ideas developed in frontier countries.

A number of studies have investigated the diffusion of technology embodied in capital goods (and used by the manufacturing sector) from advanced R&D performing economies to the rest of the world. Spending on R&D has been shown to boost productivity and growth not only in economies carrying out R&D but also other economies benefitting from international R&D spillovers.[7] No study has considered the global diffusion of medical technology and the potential welfare-enhancing benefits of medical R&D by technologically-advanced countries in terms of health improvements in less advanced economies. This should stand as a surprise because the pharmaceutical industry is the single most R&D-intensive industry, no less so than capital goods production.[8] In this paper, we propose that, similar to capital goods in manufacturing, medical goods such us pharmaceuticals (e.g. vaccines and antibiotics) or medical equipment (e.g. surgical instruments), embody R&D induced technology. Moreover, R&D in the pharmaceutical industry is highly concentrated in a small group of ten countries which are also the main exporters of these goods. In sum, it is reasonable to expect that advances in medical technology occurring in a small group of developed economies diffuse to the rest of the world either embodied in medical exports or "disembodied" in the form of flow of ideas and may, potentially, have a significant impact on health status in the rest

[7] A lengthy literature documents the importance of international R&D spillovers for capital goods; see Coe and Helpman (1995), Coe, Helpman, and Hoffmaister (1997), and Keller (2002).

[8] Lichtenberg and Virabhak (2002) also emphasize that pharmaceuticals are more R&D intensive than capital equipment imports.

of the world.

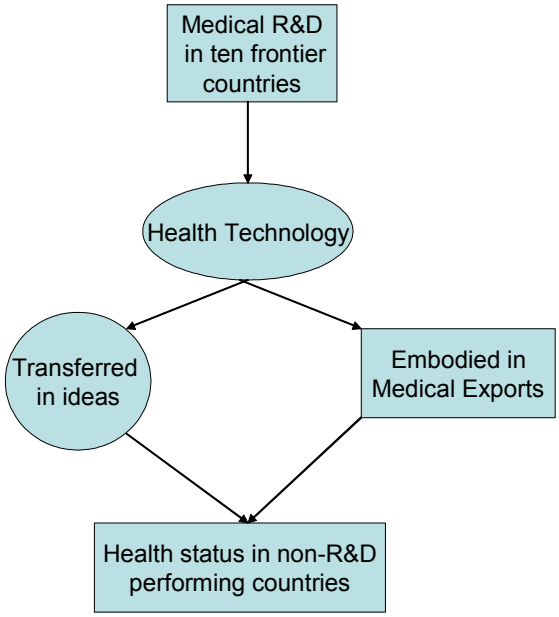
In what follows, we offer a skeletal model of the endogenous determination of health status that emphasizes the role of medical imports and foreign technology spillovers. Subsequently we assess empirically the impact of technology diffusion in determining health status. Our baseline model links health outcomes to medical technology flows embodied in imports or directly via ideas. We augment our baseline model to test the robustness of the underlying relationship. For example, it is well known that the richer an individual the greater the health inputs a person can afford and healthier individuals are more productive. Therefore we would expect health status and the level of per capita income to be closely interconnected (indeed the correlation coefficient between per capita income and life expectancy in our data is 0.77). Our empirical strategy takes account of this interconnection, first, by including (the exogenous component of) income per capita as a determinant of life expectancy and, second, by including a variety of health inputs through which income per capita might indirectly affect life expectancy (e.g. calorie intake, the number of physicians, female illiteracy rates, access to safe water, sanitation, and the number of hospital beds). In addition to these, we attempt to control for geographic and climatic conditions by including a measure of proximity to the tropics. This measure is closely related to the exogenous arrival of diseases in the theoretical framework of the next section. Finally, we perform a number of robustness checks and show that our results regarding the importance of technology flows for health status are robust. For example, we demonstrate that our estimates do not merely capture a broad "trade openness" effect, but instead depend on the degree to which a given import type embodies R&D-induced technology (see section 4 for details).

The remainder of the paper is organized as follows. Section 2 describes a rudimentary model that links medical imports and endogenous life expectancy and serves to motivate our empirical analysis. Section 3 discusses our novel dataset on medical imports and takes a first look at the correlations between medical imports and alternative indicators of health. Section 4 presents our empirical analysis and reports our main results. Section 5 concludes.

2 A model of health status and medical imports

In this section we provide a theoretical justification for our main hypothesis relating medical imports and health status. We construct a simple model in which the medical imports-health status

Figure 1: Illustration of baseline theoretical relationship



relationship emerges as an equilibrium outcome of optimal decisions by a representative agent. A novel feature of the model is that health status is determined endogenously, in contrast to most existing models where it is exogenously given.[9]

The motivation for endogenizing health status is pioneering work by Fogel (1994) and Lichtenberg and Virabhak (2002) showing that the decision to consume more medical products contributes substantially to increased longevity. According to Fogel (1994), the drastic increase in life expectancy, especially in developing countries (see Table 1), may be due to increased control by human beings over the environment. Throughout human history and until approximately two centuries ago, life expectancy was primarily exogenous. More recently, though, it has become the endogenous outcome of human decision making.

Figure 1 summarizes our hypothesis regarding medical technology diffusion. R&D in advanced countries creates medical technology which diffuses to other countries. Diffusion is either embodied

[9]Exeptions include Chakraborty (2004), Ehrlich and Chuma (1990), Grossman (1972), Hall and Jones (2004), Philipson and Becker (1998), and Usher (1973).

in medical imports and/or occurs via the direct transfer of medical knowledge and ideas. R&D expenditures in advanced countries' pharmaceutical and other health-related industries serve to enhance the technology content of specific medical products, which in due time are also imported by non-R&D performing countries.

2.1 Economic environment

We set out some simplifying assumptions to make our model tractable and focused on the relationship of interest. Particular attention is paid to constructing a model so that its reduced form can ultimately be taken to the data by means of empirical estimation. Since our primary interest is in health status in less advanced economies (the vast majority of which are not involved in medical R&D), we assume no domestic production of medical products or domestic medical R&D. Domestic agents take the frontier level of medical technology as given, choosing between imported medical inputs that will enhance their life expectancy (and their future utility) and consumption goods that enhance their current utility. This trade-off between health and consumption goods, and therefore future vs. present consumption, is the driving force of an otherwise standard neoclassical growth model.

Without loss of generality, we assume that the economy is populated by a constant number of identical agents normalized to unity. A representative agent has a finite life expectancy with conditional probability q_{t+1} of being alive at the beginning of period $t+1$. We assert this probability depends positively on an agent's "investment" in health inputs and an exogenously given rate of arrival of diseases. This is formalized as follows:

$$q_{t+1} = B \sum_{j=1}^{M_t} \frac{h_{jt}^{\gamma}}{v_t}, \;\; 0 < q < 1, \; B > 0, \; \gamma \in (0,1), \tag{1}$$

where B is an exogenous parameter, M_t is the number of health products at period t, h_{jt} is the amount of health product j at period t, γ is the share of medical product j in total health "investment" and v_t is the exogenously growing (at rate g_v) arrival of illnesses and virus mutations that reduces the probability of survival.

Equation (1) is a key equation and several points are worth noting. First, consistent with observation, the probability of being alive next period is a positive function of various exogenous effects such as genes, habits and culture which we aggregate and represent by parameter B. Second, the survival probability is negatively related to the arrival of diseases that impact the agent every

period. We consider the assumption that the arrival rate of diseases is exogenous to be quite reasonable. However, we recognize that this variable may vary from country to country, or at least from region to region, and take account of this in our empirical analysis. Finally and most importantly, we assert that the survival probability is positively related to investment in medical inputs.[10] Health inputs are incorporated in equation (1) as the sum of all amounts (h) of medical products (or varieties, M) imported.[11]

2.1.1 Household problem

Using a recursive structure the household problem can be stated as follows:

$$V(a_t) = \max_{\{c_s\}_{s=t}^{\infty}} \left\{ \sum_{s=t}^{\infty} \rho^{s-t} \left(\prod_{j=t+1}^{s} q_j \right) u(c_s) \right\} = \max_{\{c_t\}} \{u(c_t) + \rho q_{t+1} V(a_{t+1})\} \tag{2}$$

$$s.t. : w_t + r_t a_t = c_t + \sum_{j=1}^{M_t} p_{jt} h_{jt} + (a_{t+1} - a_t) \tag{3}$$

$$q_{t+1} = B \sum_{j=1}^{M_t} \frac{h_{jt}^{\gamma}}{v_t}, \tag{4}$$

$$\text{where } \{a_t, w_t, M_t, p_{jt}\}_{s=t}^{\infty} \text{ are given.} \tag{5}$$

$V(\cdot)$ is a value function, c is per capita consumption, ρ is the discount factor, w is wage, r is rent, and p_{jt} is the price of health product j at time t. The representative agent's utility maximization problem (in equation 2) differs from standard utility maximization because agents maximize the sum of their utility function appropriately discounted, conditional on the probability of survival at the end of each period. This last qualification, amounts to the additional term $\prod_{j=t+1}^{s} q_j$, that is qualitatively similar to the O-ring-function suggested by Kremer (1993). Equation (3) is the representative agent's budget constraint: it states that income from wages (w_t) and rents ($r_t a_t$) is equal to expenditures on final good consumption (c_t), health input investment $\left(\sum_{j=1}^{M_t} p_{jt} h_{jt} \right)$ and asset investment ($i_t = a_{t+1} - a_t$). A qualification is in place here. For simplicity and tractability

[10] Two clarifying comments are in place here. Throughout the paper we use the terminology "health investment" rather than "health consumption". This is to emphasize that consumption of medical goods today has only temporal (and not instantaneous) utility effects. Also, we use the terminology "medical inputs" rather than "medical goods" so as to emphasize the fact that one can think of these goods as inputs into a health production function.

[11] As mentioned, in this study we are only interested in the experiences of countries that are (primarily) medical goods importers rather than producers. Thus, we do not model medical production that takes place in ten leading economies (the overwhelming source of medical goods production and R&D) and also exclude these ten countries from empirical estimation.

we assume that when an agent dies, s/he is immediately replaced by a new born that inherits all assets (a_t) accumulated by the deceased.[12] Equation (4) is the law of motion of the conditional probability of survival discussed previously.

Optimality implies the following first-order conditions:[13]

$$u'(c_t) = \rho q_{t+1}(1 + r_{t+1})u'(c_{t+1}) \tag{6}$$

$$q'_{t+1}(h_{jt})\rho V(a_{t+1}) = \frac{B\gamma h_{jt}^{\gamma-1}}{v_t}\rho V(a_{t+1}) = p_{jt}\, u'(c_t), \tag{7}$$

where $q'_{t+1}(h_{jt}) = \frac{\partial q_{t+1}}{\partial h_{jt}}$. Using equations (2), (6) and (7) yields the Euler equation

$$(1 + r_{t+1})\frac{q_{t+1}}{q'_{t+1}(h_{jt})} = \frac{1}{p_{jt}}\frac{u(c_{t+1})}{u'(c_{t+1})} + \frac{p_{jt+1}}{p_{jt}}\frac{q_{t+2}}{q'_{t+2}(h_{jt+1})}. \tag{8}$$

The difference between equation (8) and the standard neoclassical Euler equation is the appearance of the probability of survival (q). Put differently, if we set $q = 1$ (the neoclassical model assumption), equation (8) reduces to the standard Euler equation.

2.2 Consumption good production

In our model, the only good that provides utility to consumers is produced with a Cobb-Douglas intensive production technology that is given by (assuming constant population we set it as numeraire; i.e. $L_t = 1$)

$$y_t = k_t^{\alpha} A_t^{1-\alpha}, \tag{9}$$

where y is output per capita, k is capital per capita, A is a labor-augmenting productivity parameter that grows exogenously at rate g_A, and α is the capital share. Assuming a competitive market, the wage (w) and rental rate (r) are given by

$$w_t = (1 - \alpha)y_t \tag{10}$$

$$r_t = \alpha\frac{y_t}{k_t} - \delta, \tag{11}$$

where δ is a constant capital depreciation rate.

[12] This assumption is made for simplicity. With this assumption everyone in the economy is alike in the sense that they share the same value of the state variable.

[13] In models with an endogenous discount factor, the optimization problem may not be well-defined and problems with the second order conditions may arise. This is not a concern here because Stern (2003) has proved the existence of a solution to an optimization problem such as ours.

2.3 Characterization of the aggregate economy

The aggregate economy is characterized by the following system of equations:

$$
\begin{aligned}
u'(c_t) &= \rho q_{t+1}(1+r_{t+1})u'(c_{t+1}) && \text{(S1)}\\
\frac{\rho B\gamma h_{jt}^{\gamma-1}}{v_t}V(a_{t+1}) &= p_{jt}\,u'(c_t); \qquad a_t = k_t && \text{(S2)}\\
q_{t+1} &= B\frac{\sum_{j=1}^{M_t} h_{jt}^{\gamma}}{v_t} && \text{(S3)}\\
k_{t+1} &= i_t + (1-\delta)k_t && \text{(S4)}\\
y_t &= k_t^{\alpha}A_t^{1-\alpha} && \text{(S5)}\\
y_t &= c_t + i_t + \sum_{j=1}^{M_t} p_{jt}h_{jt} && \text{(S6)}\\
w_t &= (1-\alpha)y_t && \text{(S7)}\\
r_t &= \alpha\frac{y_t}{k_t} - \delta && \text{(S8)}
\end{aligned}
$$

$$
q_0,\ v_0,\ h_0,\ k_0,\ A_0 \ \text{ given.} \qquad (12)
$$

Equations (S1-S2) are the two first-order conditions from the household optimization problem. Equation (S3) is the survival probability equation, (S4) is the law of motion of capital and (S5) the aggregate production function. Equation (S6) is the expenditure equation which states that, in addition to final good consumption and investment in physical capital, agents spend part of their income on medical inputs. Finally, equations (S7-S8) show input prices determined by competitive conditions.

2.4 Steady-state

Assuming a constant-rate-of-risk-aversion utility function, $u(c_t) = c_t^{1-\sigma}/(1-\sigma)$, where σ is the inverse of the intertemporal elasticity of substitution, the model yields the Euler equation for consumption goods as

$$
(1+g_A) = [\rho q^*(1+r^*)]^{1/\sigma}\,, \qquad (13)
$$

and the Euler equation for health products as

$$
\frac{c^*}{M^*} = \frac{1-\sigma}{\gamma^2}\frac{r^*-g_A}{1+g_A}h^*, \qquad (14)
$$

and the probability of survival as

$$q^* = B\,(M^*/v^*)\,h^{*\gamma} = B(M^*h^*)^{\gamma}(M^*)^{1-\gamma}/v^*, \tag{15}$$

where (*) denotes steady state values.[14] Equation (15) shows that, in the steady state, the probability of survival, q^*, is positively related to imports of medical products $[(M^*h^*)^{\gamma}$ or the product of medical varieties and their corresponding amounts scaled by parameter $\gamma]$, a medical R&D externality $[(M^*)^{1-\gamma}$ or the number of medical varieties innovated abroad but used domestically scaled by $1-\gamma]$,[15] and a parameter (B) that may reflect exogenous effects of institutions, culture, and policy. In addition, the probability of survival is negatively related to the arrival rate of viruses, v.

Equation (15) establishes a relationship between health status and medical imports that motivates our empirical analysis. The logarithmic version of (15) yields our baseline testable equation

$$\ln q_i = a_0 - a_1 \ln v_i + a_2 \ln(hM)_i + a_3 \ln M_i + \varepsilon_i, \tag{16}$$

where q_i (the probability of survival) is captured by health status in country i, v_i (the arrival of diseases) is captured by a country's geographic proximity to the tropics, $(hM)_i$ represents imports of health products embodying medical technology, M_i represents direct medical R&D spillovers to the non-frontier country via knowledge flows from frontier countries, and ε_i is a random error. In implementing (15) empirically we represent steady-state values of the variables via their empirical long-run averages and, thus, we have omitted the (*) superscript in (16). Equation (16) is the baseline model we estimate after we discuss data construction in the next section.

3 Data description

We describe the data set we have assembled to test our main hypotheses and take a first look at the relationship of health with medical imports and foreign medical R&D. The focus of our study, the probability of survival, is measured by three variables reflecting a country's health status: life expectancy at birth, the rate of male mortality and the rate of infant mortality.

[14] A detailed derivation of the Euler and steady-state equations appears in the appendix.

[15] This externality is common in product variety-based R&D growth models (e.g. Romer (1990)) and is due to the complementarity among medical inputs. This reflects the benefit of spreading a given total of inputs, Mh_j, over a wider range, M. The benefit arises because of diminishing returns to each of the h_j individually. The assumption that $\gamma < 1$ is necessary for this type of externality to exist. The smaller the value of γ the larger the complementarity among inputs and the higher the externality.

Table 2: Categories of imported medical products used in estimation

Medicinal & Pharmaceutical Products (54)	Hyg. & Pharm. Articles of Rubber (6281)
Electric Apparatus for Medical Purposes (774)	Orthopaedic Appl., Surg. Belts & the like (8996)
Medical Instruments & Appliances (872)	Optical Goods (884)
Medical, Dental, Surg. or Vet. Furniture (82121)	Insecticides (5911)
Laboratory, Hyg. & Pharm. Glassware (66581)	

Notes: Medicinal and Pharmaceutical Products include, among others, the following sub-categories: Antibiotics (5413), Antisera and Microbial Vaccines (54164), and Medicaments containing Antibiotics and derivatives thereof (54171).

We employ three main sources of data. First, the OECD *International Trade by Commodity Statistics* (ITCS) database contains medical-related exports (in current $US) from each of the ten leading innovators of medical technology (Belgium, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the U.K., and the U.S.) to each of the importing countries. These ten countries supply the bulk of medical products and carry out the vast majority of medical R&D. We use this data set to measure a country's imports of medical inputs because it is the only consistent source of medically-related trade. The ITCS database includes annual bilateral flows across 269 international locations for 2581 goods categories (with a great deal of missing observations) for the period 1960-2000. We inspected this list of traded goods categories independently, consulting bio-specialists when in doubt, to come up with a list of thirteen health related traded goods sub-categories. We excluded four of these categories for which data availability was a serious concern[16] and were left with the nine categories reported in Table 2 (with *SITC Revision 2* codes in parentheses). Our final trade dataset contains exports of each of the nine categories from each of the ten "medical frontier" countries to each of seventy-three "non-frontier" countries.

Initially, we consider an aggregate measure of a country's medical imports as the sum of all the pharmaceutical, medical, and health-related categories reported in Table 2. In addition to our aggregate measure of medical imports we also consider a measure of medical capital and equipment as the sum of two categories: Electric Apparatus for Medical Purposes (SITC code 774) and Medical Instruments & Appliances (SITC code 872). Finally, we also consider a third measure of medical

[16]These categories were: Soap, organic surface-active products and preparations (5541), Sinks, wash basins, bidets, water closet pans, etc (8122), Disinfectants packed for sale etc. (59141), and Preparations culture media for development of micro-organisms (59893).

imports: medicinal and pharmaceutical imports alone (SITC code 54). To convert figures from current to constant (1990) dollars, we use the manufacturing and chemicals industry price deflator (for each of the ten providers of medical goods) extracted from the 1998 OECD *Intersectoral Database* (ISDB 1998).[17] Finally, our measure of real medical imports is converted to a per capita basis by dividing by each recipient's total population.

Second, to construct our measure of foreign medical innovation and the spillover effect we use the *ANBERD* 2001 database for pharmaceutical R&D in eight technologically advanced countries (the ten listed above minus Belgium and Switzerland for which no R&D data exist) from 1973 to 1997. These eight countries account for the vast majority of OECD (and thus global) medical R&D: they accounted for 96 percent of all medical R&D expenditures reported to the OECD in 1973 and for 94 percent in 1995. The Commission on Macroeconomics and Health (2001, p. 79) notes the so called *90/10 disequilibrium* in medical R&D spending: only 10 percent of R&D spending is directed at diseases pertinent to 90 percent of the global population. It would seem, *a priori*, that most R&D spending in the leading economies ought not have an impact on health in non leading economies. Two points are worth mentioning here. While the disequilibrium may exist so that most medical R&D is directed at Type I diseases (incident in both rich and poor countries e.g. measles, hepatitis B, diabetes tobacco-related illnesses) or Type II diseases (incident in both rich and poor but prevalent in poor, e.g. HIV/AIDS and tuberculosis), such R&D may have an impact on health in lower income economies, an empirical issue to which our paper is addressed. Second, the significant estimates of medical R&D on health in less advanced economies uncovered by our empirical estimation (see next section) should be seen as 'lower bounds' on the effects of medical R&D: any reallocation of R&D resources (as urged by the Commission) will likely bring substantially greater health benefits to non leading economies.

Our R&D expenditures measure is the current PPP dollars series for (SIC Revision 2) category "Drugs and Medicines" for the eight leading economies.[18] We deflate these by the chemical industry price deflators from the *ISDB* database. Finally, we construct a measure of medical R&D flow for each non-frontier country by multiplying R&D in constant US dollars of each of the eight source

[17] We use the chemical industry price deflator for pharmaceuticals imports and the manufacturing sector price deflator for other types of medical imports.

[18] R&D spending on other medical products is only available at an aggregate level that includes a broad set of non-medical categories such as Electric Machinery excluding Communications Equipment, and Professional Goods, which would be rather imperfect matches for R&D on Electric apparatus for medical purposes and for Medical instruments and appliances, respectively.

countries by the value share of exports of that source country in total medical exports to the recipient country. That is, country i's medical R&D flow is:

$$PHARD_{it} = \sum_{c=1}^{8} \frac{PHAEX_{cit}}{\sum_{c=1}^{8} PHAEX_{cit}} \times CRD_{ct}, \tag{17}$$

where $PHAEX_{ci}$ is pharmaceuticals exports by source country c to destination country i, and CRD_c is pharmaceutical R&D expenditures by source country c.[19]

One potential concern with our imports-weighted R&D measure is that it captures trade-related effects rather than the disembodied flow of ideas. However, the correlations between *PHARD* and the medical imports measures are very low (-0.03 with medical imports, 0.11 with medical capital and equipment imports, and -0,08 with pharmaceutical imports); it is, thus, unlikely to capture trade-related effects.[20] Moreover, in the empirical analysis we include medical imports as a separate variable along with *PHARD* in all estimated models; this helps to isolate the effects of foreign medical R&D from potential trade-related effects. The fact that both variables appear to be independently significant determinants of health status (see next section), along with the low correlations between *PHARD* and the imports measures, suggests that the weights employed to construct *PHARD* capture 'non-trade' factors (e.g. institutional, cultural, linguistic and physical proximity between locations) that enhance the flow of ideas from one location to another.

Third, we use a number of health output and health input variables from various sources. The *World Development Indicators* (WDI) 2002 database provides data on life expectancy at birth, infant mortality per thousand live births, male mortality per thousand male adults, physicians per thousand people, the female illiteracy rate,[21] the percentage of population with access to an improved water source,[22] sanitation,[23] and hospital beds per thousand people. The WDI also

[19] In the cross-sectional empirical application of the next section, we use the average of this variable over the period, a measure closely connected to the level of the medical R&D stock of each country. This foreign R&D measure is similar in spirit to the one used in the capital-goods technology diffusion literature and has little cross-sectional variation. It varies across different importing countries to the degree that one country imports more from a more-R&D intensive source country rather than a less R&D intensive country.

[20] In order to create a variable that captures trade-related technology flows, Coe *et al.* (1997) construct an additional variable by interacting the imports-weighted R&D variable with a general indicator of openness.

[21] Defined as the percentage of females ages 15-24 who cannot, with understanding, read and write a short simple statement on their everyday life.

[22] Access to an improved water source refers to the percentage of the population with reasonable access to an adequate amount of water from an improved source, such as a household connection, public stand-pipe, borehole, protected well or spring, and rainwater collection. Reasonable access is defined as the availability of at least 20 liters per person a day from a source within one kilometer of the dwelling.

[23] Defined as the percentage of the population with access to improved sanitation facilities.

provides data on total population and GDP per capita in PPP dollars. We also obtained data on daily calorie intake from the *Food Balance Sheets* database of the Food and Agriculture Organization (FAO). We construct total daily calorie intake per person as the sum of calorie intake from both vegetable and animal sources. Data on each country's geographic latitude (proximity to the tropics) is from Hall and Jones (1999). Finally, in robustness checks, we use two broad indicators of openness: the log of the number of years during which a country is open from Hall and Jones (1999) and the log of the Frankel and Romer (1999) predicted trade share computed from a gravity model based only on population and geography.

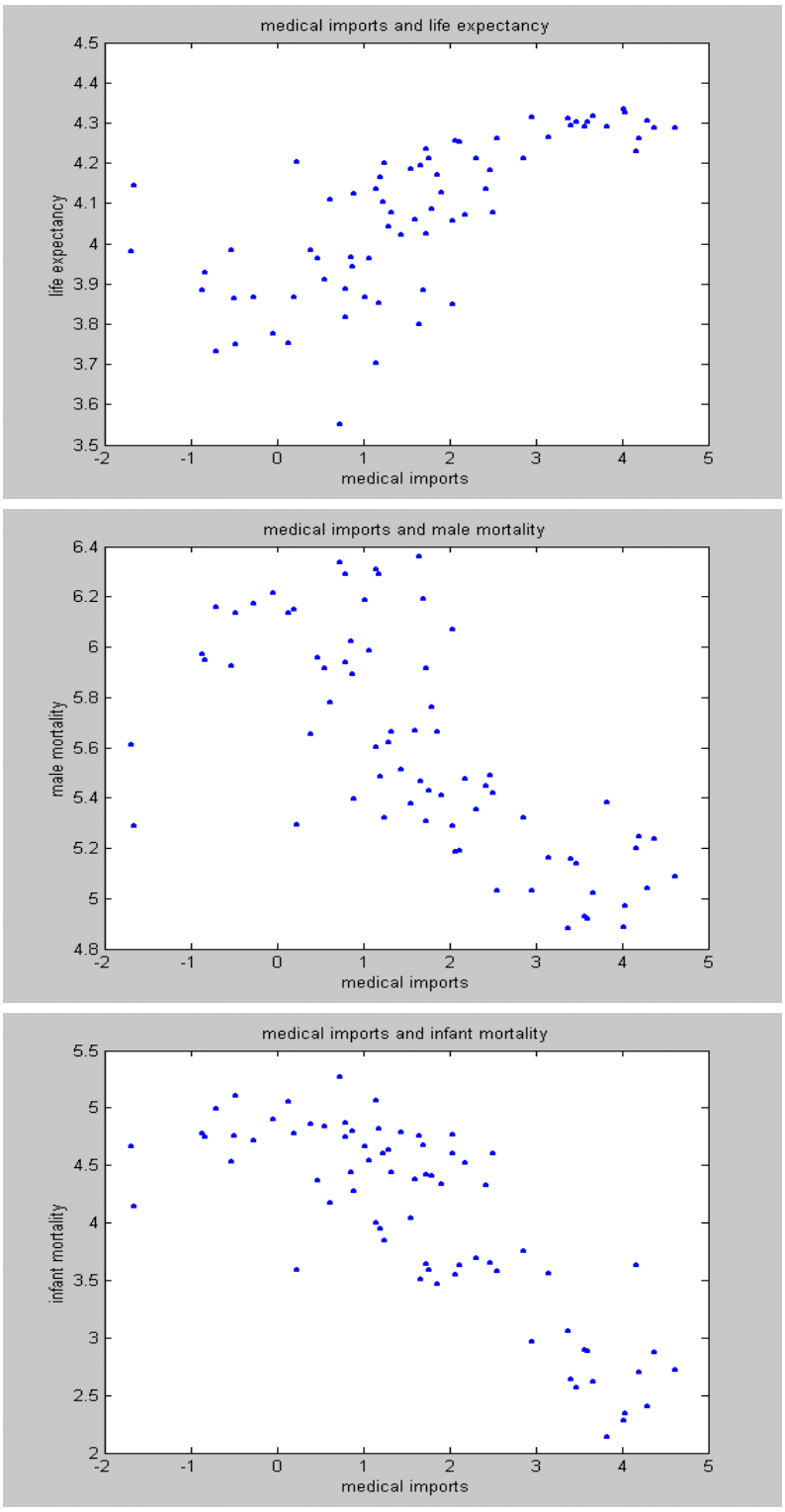
We were able to put together all the above series for 73 countries (excluding the ten countries listed previously that are the leading source of pharmaceutical production and R&D) during the period 1961-1995. However, the great majority of these series are not available annually; in some cases the data are exceedingly sparse in the time dimension.[24] Because the cross-sectional dimension of the dataset is more complete (with data available in all 73 countries for most variables)[25] and, more importantly, because of the inherent long-run nature of the relation under study, we chose to explore empirically the cross-sectional dimension of our dataset. We do, however, report panel results as a robustness check on our cross section results. The aforementioned data limitations did not allow us to exploit fully the dynamic aspects of the panel.

The cross sectional variables are measured as long-run averages (over the 1961-95 period) of the available data. Table A1 contains information on the mean value of the main variables by country. Scatter plots between medical imports and health are in Figure 2. The first panel shows a positive correlation between aggregate medical imports and life expectancy (the correlation coefficient is 0.71). The correlation between medical imports and health is robust to the choice of health indicator: the other two panels show scatter plots between medical imports, on the one hand, and male and infant mortality rates, on the other (the correlation coefficients are -0.73 and -0.79, respectively). In the following section we examine systematically the health-medical imports relationship.

[24] Life expectancy and infant mortality rates are available about every other year, male mortality rates are available about once per decade, calorie intake about twice per decade, and physicians about a third of the time. Moreover, water and sanitation are available about one tenth of the time for most countries, the variable hospital beds is available about twenty percent of the time, and the two openness variables are available only once per country during this period.

[25] One variable for which we have several missing countries in the cross-section is female illiteracy whose availability is restricted to 62 of the 73 countries in our complete sample.

Figure 2: Scatter plots between measures of health and medical imports



Notes: The correlation between medical imports and life expectancy, male mortality and infant mortality are, 0.71, -0.73 and -0.79, respectively.

4 Empirical results

4.1 Preliminary evidence

We measure health status by three indicators: average life expectancy at birth (*LIFE*), infant mortality (*INFANT*) and male mortality (*MALE*). In Table 3 we report the cross sectional unconditional correlations.[26] All variables are in natural logs.

Health status has a strong correlation with our aggregate measure of medical imports (*MEDIM*) that includes, pharmaceuticals, imports of medical equipment and other broadly defined medical imports (all the categories listed in Table 2): the correlation of *MEDIM* with life expectancy, infant mortality, and male mortality is 0.71, -0.79, and -0.73, respectively. In addition we consider two other measures of medical imports, per capita pharmaceutical imports (*PHAIM*) and (per capita) imports of medical capital and equipment (*MCAPIM*): the correlation between *PHAIM* and the three health indicators is 0.65, -0.74 and -0.68, respectively, and between *MCAPIM* and the three health indicators is even higher (0.83, -0.88 , and -0.83, respectively).

One might argue that, to a large extent, the high correlations between medical imports and health outcomes are due to the positive effect of per capita income on both variables. For example, the correlation of GDP per capita with *LIFE* is 0.77 and with *MEDIM* is 0.81. In the next section, we control for this by including the exogenous component of per capita income and we also include a number of health inputs through which income may determine health outcomes. Table 3 shows that health inputs, such as calorie intake per person (*CAL*), the number of physicians per thousand people (*PHYSI*), and access to an improved water source (*WATER*) are also strongly correlated with life expectancy (correlation coefficients of 0.79, 0.90, 0.79 respectively). We also consider the rate of female illiteracy (*ILLIT*, correlation with life expectancy = -0.82) and proximity to the tropics (*TROP*, correlation with life expectancy = -0.49) and include all these variables as potential determinants of life expectancy.

Our main hypothesis is that medical imports embody foreign health technologies developed through R&D in the advanced countries. In addition, a complementary hypothesis is that health technologies developed in advanced economies diffuse to the rest of the world in the form of ideas,

[26] As mentioned previously, our sample includes 73 countries but excludes the ten countries (Belgium, France, Germany, Italy, Japan, Netherlands, United Kingdom, United States, Switzerland and Sweden) with a substantial domestic pharmaceutical sector (effectively, the top ten pharmaceutical exporting nations) in order to focus on health status in countries that depend on imports of foreign medical technology.

Table 3: Unconditional cross-sectional correlations

	MEDIM	MCAPIM	PHAIM	PHARD	TROP	CAL	PHYSI	ILLIT	WATER	LIFE	INFANT	MALE	INC
MEDIM	1												
MCAPIM	0.95	1											
PHAIM	0.99	0.92	1										
PHARD	-0.03	0.11	-0.08	1									
TROP	-0.46	-0.51	-0.42	0.02	1								
CAL	0.78	0.85	0.74	-0.03	-0.55	1							
PHYSI	0.71	0.83	0.65	0.31	-0.59	0.82	1						
ILLIT	-0.53	-0.70	-0.47	-0.43	0.28	-0.67	-0.71	1					
WATER	0.68	0.77	0.64	0.17	-0.48	0.73	0.78	-0.56	1				
LIFE	0.71	0.83	0.65	0.31	-0.49	0.79	0.90	-0.82	0.79	1			
INFANT	-0.79	-0.88	-0.74	-0.10	0.49	-0.85	-0.81	0.89	-0.73	-0.89	1		
MALE	-0.73	-0.83	-0.68	-0.22	0.56	-0.81	-0.89	0.73	-0.73	-0.94	0.86	1	
INC	0.81	0.86	0.77	0.17	-0.53	0.77	0.80	-0.59	0.69	0.77	-0.82	-0.78	1

Notes: All variables are in natural logarithms. The sample size used here is 68 countries, except for ILLIT. MEDIM is aggregate medical imports in constant $US per person, MCAPIM is imports of medical machinery and equipment in constant $US per person, PHAIM is pharmaceutical imports in constant $US per person, PHARD is import-country-specific pharmaceutical -industry R&D in millions of constant dollars implied by R&D of source country multiplied by import share of that source country in total medical imports from 8 source counries for which R&D data are available, TROP is tropical proximity defined as the inverse of the absolute value of latitude, CAL is total calories per person, PHYSI is number of physicians per thousand people, ILLIT is illiteracy rate as a percentage for females ages 15 to 24, WATER is percentage of population with access to improved water source, LIFE is life expectancy, INFANT is infant mortality, MALE is male mortality and INC is GDP per capita in constant $US.

not necessarily embodied in physical imports. In order to evaluate this, we constructed the variable *PHARD* (defined in the previous section). The implicit assumption is that a non-R&D performing country's health knowledge is implied by the health technology of the countries it trades with (in the form of medical imports); consequently greater trade intensity with countries that perform large amounts of medical R&D will increase a country's health knowledge. The presumption is that the trade weights used in the construction of *PHARD* capture physical, cultural, linguistic, and institutional proximity between countries, all of which would enhance technology flows, independently of the effect of trade through the embodied technology channel, for which we control separately in each estimated model (see next section). Table 3 shows that *PHARD* is also correlated with health outcomes but less so than the physical imports measures: the correlation with life expectancy is 0.31, and with infant and male mortality -0.10 and -0.22, respectively.

4.2 Cross-section regression results

The correlations in Table 3 provide only suggestive evidence. In this section we control for a variety of determinants of health status to test systematically the link between imports of health technology and health status. For example, and as mentioned previously, the positive correlation between medical imports and health could be due to the positive effect of per capita income on both variables. Consequently, in the regression model we control for income per capita and also include a number of health inputs through which income may affect health. To control for per capita income we include the exogenous component of income per person to account for the endogeneity between income and health status. We obtain the exogenous component of income as that part explained in a regression of income per capita on social infrastructure (*GADP*). Social infrastructure is the measure assumed by Hall and Jones (1999) to be the main determinant of per capita income across a wide cross section of economies. *GADP* is an index of government anti-diversion policies and measures the role of the government in preventing rent-seeking and other non-wealth creating activities, as well as the role of government as a possible diverter of private wealth. We believe that GADP determines per capita income but is, itself, not determined by the health level or, equivalently, it is exogenous to health status. *GADP* is a positive and significant determinant of per capita income (estimated coefficient of 2.88 and t-statistic = 8.12) and explains 46 percent of the variation in per capita income.

Our main measure of health is life expectancy; this is the measure used by most studies.[27] All variables are considered in natural logs so our estimates can be interpreted as elasticities. We report results in the first panel of Table 4 with *MEDIM* as the indicator of medical technology imports. In addition to the aggregate measure of medical imports, we look at two alternatives: medical capital and equipment (*MCAPIM*) in the second panel, and pharmaceutical imports (*PHAIM*) in the third panel of Table 4.

We estimate a number of alternative specifications. All specifications include the exogenous component of per capita income to allow for general level of development effects on life expectancy. Models (1) and (2) include our measures of medical technology diffusion. Model (3) is the baseline regression equation: it tests empirically equation (16) where hM is proxied by medical imports (*MEDIM* in panel 1), M is proxied by implied foreign R&D (*PHARD*), and the arrival of diseases, v, is approximated by a country's geographic proximity to the tropics (*TROP*). The other specifications (models 4-7) include additional determinants of life expectancy to gauge the robustness of our estimates.

The results in the first panel of Table 4 support the existence of both an embodied medical technology link via imports of medical products and a disembodied medical technology diffusion link via the direct flow of ideas: the estimate of *MEDIM* is positive and significant in all specifications (except model (5) where it is marginally insignificant, p-value = 0.12), and so is that of *PHARD* in models 2-5. The estimate of the elasticity of life expectancy with respect to medical imports is between 0.012 and 0.056 across the various specifications: an increase in medical imports by 10 percent results in an increase in life expectancy by between 0.12 and 0.56 percent. While these elasticities may seem low, we note that a 10 percent increase in per capita income is associated with an increase in life expectancy of between 0.32 to 1.46 percent. The elasticity of medical imports is consistently about one third that of per capita income so that a 10 percent increase in income per capita will have an equivalent impact on life expectancy as a 30 percent increase in medical imports. While the former increase may be difficult to envisage, at least in the short run, the second increase is not beyond the bounds of feasible public policy, even in the shorter term.

The elasticity of life expectancy with respect to *PHARD* ranges from 0.16 for models (2) and (3) to a (statistically insignificant) 0.03 in models (6) and (7). We note that this elasticity is

[27] It should be noted that the correlation between the three indicators of health status is high. While we focus on life expectancy, we will also discuss the implications of medical imports on the other two indicators of health status and highlight possible differences between the three measures.

Table 4: Cross-country life expectancy regressions

Specif. 1	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MEDIM	.0558*	.0537*	.0499*	.0288**	.0123[1]	.0158**	.0144***
	(3.68)	(3.92)	(3.91)	(2.05)	(1.59)	(1.99)	(1.88)
INC	.1362*	.1463*	.1351*	.0825*	.0671*	.0367	.0318
	(3.97)	(4.28)	(4.31)	(2.51)	(3.08)	(1.35)	(1.18)
PHARD	—	.1602*	.1597*	.1596*	.0615*	.0347	.0330
		(5.53)	(5.67)	(6.01)	(2.55)	(1.05)	(1.02)
TROP	—	—	−.0214**	−.0076	.0133***	.0069	.0073
			(−2.07)	(−0.93)	(1.92)	(1.05)	(1.11)
CAL	—	—	—	.4727*	.1057	.0246	.0208
				(4.14)	(1.07)	(0.24)	(0.20)
PHYSI	—	—	—	—	.0867*	.0659*	.0634*
					(6.74)	(4.06)	(3.78)
ILLIT	—	—	—	—	—	−.0369*	−.0374*
						(−2.95)	(−3.01)
WATER	—	—	—	—	—	—	.0172
							(0.64)
Adj. R^2	58.8	70.5	71.5	76.4	83.9	86.2	86.0
Obs.	72	72	72	70	70	59	59

Specif. 2	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MCAPIM	.0814*	.0682*	.0643*	.0419*	.0169***	.0200**	.0191**
	(5.99)	(5.38)	(5.16)	(2.67)	(1.72)	(2.07)	(1.96)
INC	.0621***	.0937*	.0894*	.0630***	.0604*	.0355	.0342
	(1.86)	(2.74)	(2.80)	(1.79)	(2.75)	(1.35)	(1.29)
PHARD	—	.1237*	.1261*	.1393*	.0556**	.0282	.0279
		(4.65)	(4.78)	(5.05)	(2.34)	(0.91)	(0.91)
TROP	—	—	−.0159[2]	−.0048	.0139**	.0082	.0084
			(−1.61)	(−0.60)	(2.03)	(1.23)	(1.25)
CAL	—	—	—	.3968*	.0873	−.0004	−.0012
				(3.28)	(0.85)	(−0.004)	(−0.01)
PHYSI	—	—	—	—	.0848*	.0659*	.0652*
					(6.65)	(4.11)	(3.89)
ILLIT	—	—	—	—	—	−.0349*	−.0352*
						(−2.74)	(−2.75)
WATER	—	—	—	—	—	—	.0068
							(0.26)
Adj. R^2	68.9	75.2	75.5	78.2	84.7	86.8	86.6
Obs.	73	73	73	71	71	60	60

Specif. 3	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
PHAIM	.0433*	.0463*	.0431*	.0235***	.0100[2]	.0135***	.0127***
	(2.79)	(3.23)	(3.21)	(1.68)	(1.41)	(1.80)	(1.74)
INC	.1695*	.1674*	.1546*	.0940*	.0714*	.0457***	.0430***
	(4.75)	(4.87)	(4.89)	(2.89)	(3.36)	(1.68)	(1.58)
PHARD	—	.1748*	.1741*	.1694*	.0636*	.0399	.0390
		(6.28)	(6.39)	(6.59)	(2.62)	(1.19)	(1.19)
TROP	—	—	−.0224**	−.0078	.0136***	.0077	.0079
			(−2.06)	(−0.95)	(1.96)	(1.15)	(1.20)
CAL	—	—	—	.4879*	.1039	.0201	.0171
				(4.29)	(1.05)	(0.19)	(0.16)
PHYSI	—	—	—	—	.0884*	.0683*	.0668*
					(7.00)	(4.23)	(4.01)
ILLIT	—	—	—	—	—	−.0361*	−.0364*
						(−2.89)	(−2.91)
WATER	—	—	—	—	—	—	.0108
							(0.41)
Adj. R^2	56.7	70.5	71.5	76.9	84.6	86.8	86.5
Obs.	73	73	73	71	71	60	60

Notes: * p-value <0.01, ** p-value<0.05, *** p value<0.10, [1]p-value = 0.118, [2]p-value = 0.165.
Heteroskedasticity-consistent finite sample standard errors are used in constructing t-statistics.

robust across models (2)-(4) but is more than halved once we account for the number of physicians (*PHYSI*) in model (5). Greater availability of physicians is one of the main means through which the ideas channel operates, and including the number of physicians captures in part this channel. This may account for the reduction in the value of the estimate of *PHARD* in models (5)-(7).

The exogenous component of per capita income has a positive impact on health in specifications (1)-(5). Nevertheless, once we control for calorie intake (*CAL*) and number of physicians in model (5), its magnitude falls by half; this suggests that income affects life expectancy in large part via its impact on calorie consumption and medical care. When we also account for female illiteracy (*ILLIT*), the estimated coefficient for income per capita is less than one third of its original value and becomes statistically insignificant. Per capita income is probably the most commonly suggested explanation for differences in health status across countries. Our results suggest that per capita income level is indeed one of the main determinants of health but the strong effect can be explained, in large part, once we introduce additional health inputs (such us calorie intake, physician availability and female education) through which income affects life expectancy. On the other hand, the significant effect of medical imports on life expectancy remains robust even when account is taken of additional health inputs.

Proximity to the tropics (*TROP*) has a negative effect on life expectancy in model (3), our baseline specification. In models (4) and (5) we introduce two other health inputs: food consumption[28] measured by calorie intake and medical care availability measured by the number of physicians per thousand people. Both have a strong positive impact on life expectancy: the elasticity estimate of *CAL* is the largest among all explanatory variables (0.473 in model 4) but it decreases and becomes insignificant once we account for physicians and illiteracy in models (5) and (6). The elasticity with respect to physicians in model (5) is 0.087 and decreases to 0.063, but remains strongly significant, even after we control for female illiteracy and access to safe water (*WATER*) in models (6) and (7).

In model (6), illiteracy of young women has a significant impact on life expectancy with an estimated elasticity of -0.037. One of the oft-cited propositions in the development literature is

[28] We recognize that food is of dual usage, i.e. both a consumption and health good. Even though we do not allow for this in the theoretical model, we allow calorie intake to enter as a regressor in our empirical specification of health status to capture the marginal impact of food consumption on health. This should be positive for countries below the very top income percentile since over-consumption of food (which can have a negative marginal impact on health in the richer countries) is less likely to be a problem for the 73 countries studied here. Over-consumption of food will be relevant for the richer countries, excluded for the most part in this analysis as they also happen to be the top R&D performers. This non-linearity of the marginal impact of calorie-intake on health is thus left unexplored in the current study.

Table 5: Cross-country male mortality regressions

Specif. 1	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MEDIM	−.1376*	−.1343*	−.1173*	−.0644**	−.0351[1]	−.0402[2]	−.0453[3]
	(−4.49)	(−4.63)	(−5.19)	(−2.33)	(−1.41)	(−1.44)	(−1.65)
INC	−.2665*	−.2869*	−.2475*	−.0957	−.0735	−.0593	−.0761
	(−3.68)	(−3.84)	(−3.88)	(−1.31)	(−1.14)	(−0.69)	(−0.87)
PHARD	—	−.2649*	−.2703*	−.2592*	−.0624	−.0014	−.0071
		(−3.75)	(−4.03)	(−4.01)	(−0.96)	(−0.01)	(−0.07)
TROP	—	—	.0981*	.0632*	.0199	.0266	.0276
			(3.71)	(2.98)	(1.11)	(1.25)	(1.27)
CAL	—	—	—	−1.192*	−.3912	−.2322	−.2488
				(−4.67)	(−1.43)	(−0.77)	(−0.81)
PHYSI	—	—	—	—	−.1741*	−.1545*	−.1639*
					(−5.03)	(−3.19)	(−3.34)
ILLIT	—	—	—	—	—	.0515	.0498
						(1.31)	(1.27)
WATER	—	—	—	—	—	—	.0649
							(0.85)
Adj. R^2	58.3	64.6	69.7	74.7	80.7	75.9	75.6
Obs.	70	70	70	68	68	57	57

Specif. 2	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MCAPIM	−.1890*	−.1719*	−.1514*	−.1002*	−.0556**	−.0621***	−.0732**
	(−6.85)	(−6.25)	(−6.92)	(−3.25)	(−1.98)	(−1.93)	(−2.29)
INC	−.1025	.1459**	−.1317**	−.0417	−.0407	−.0344	−.0481
	(−1.53)	(−2.08)	(−2.23)	(−0.58)	(−0.65)	(−0.44)	(−0.63)
PHARD	—	−.1634*	−.1815*	−.2031*	−.0402	.0249	.0236
		(−2.59)	(−3.02)	(−3.24)	(−0.65)	(0.27)	(0.25)
TROP	—	—	.0853*	.0581*	.0204	.0268	.0284
			(3.64)	(2.94)	(1.19)	(1.28)	(1.34)
CAL	—	—	—	−.9807*	−.3402	−.1617	−.1746
				(−3.63)	(−1.24)	(−0.55)	(−0.59)
PHYSI	—	—	—	—	−.1626*	−.1457*	−.1555*
					(−4.82)	(−3.04)	(−3.24)
ILLIT	—	—	—	—	—	.0472	.0445
						(1.19)	(1.13)
WATER	—	—	—	—	—	—	.0845
							(1.28)
Adj. R^2	68.4	70.4	74.0	76.7	81.6	77.1	77.1
Obs.	71	71	71	69	69	58	58

Specif. 3	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
PHAIM	−.1149*	−.1201*	−.1051*	−.0569**	−.0338[4]	−.0394[5]	−.0441***
	(−3.92)	(−4.32)	(−4.86)	(−2.27)	(−1.57)	(−1.64)	(−1.91)
INC	−.3249*	−.3255*	−.2802*	−.1108	−.0753	−.0640	−.0785
	(−4.66)	(−4.66)	(−4.73)	(−1.61)	(−1.24)	(−0.79)	(−0.98)
PHARD	—	−.2923*	−.2958*	−.2745*	−.0672	−.0083	−.0132
		(−4.39)	(−4.65)	(−4.49)	(−1.05)	(−0.09)	(−0.13)
TROP	—	—	.1005*	.0647*	.0212	.0278	.0291
			(3.67)	(3.02)	(1.19)	(1.32)	(1.35)
CAL	—	—	—	−1.213*	−.3954	−.2299	−.2511
				(−4.78)	(−1.47)	(−0.77)	(−0.83)
PHYSI	—	—	—	—	−.1738*	−.1544*	−.1636*
					(−5.27)	(−3.36)	(−3.50)
ILLIT	—	—	—	—	—	.0515	.0501
						(1.33)	(1.30)
WATER	—	—	—	—	—	—	.0657
							(0.88)
Adj. R^2	56.8	64.7	69.9	75.2	81.3	76.8	76.6
Obs.	71	71	71	69	69	58	58

Notes: * p-value <0.01, ** p-value<0.05, *** p value<0.10, [1]p-value = 0.164, [2]p-value = 0.157, [3]p-value = 0.105, [4]p-value = 0.122, [5]p-value = 0.107. Heteroskedasticity-consistent finite sample standard errors are used in constructing t-statistics.

the link between female literacy and health; our evidence confirms this proposition. We note that when we include *ILLIT* sample size is reduced by 11 observations. Also the estimated elasticity of life expectancy with respect to *MEDIM* is higher (and now statistically significant) in model (6). Interestingly, a comparison of the correlation between imports and health status for this smaller sample shows that the unconditional correlations are lower in the smaller sample of model (6).[29] This suggests that the higher estimate for the impact of imports on health status in model (6) is not due to sample specificity but rather due to the inclusion of an important determinant of health status. Model (6) explains about 86 percent of the cross-sectional variation in life expectancy.

Adding access to an improved water source in model (7) does not alter the magnitude and significance of the coefficient estimates and is, itself, statistically insignificant. When, however, we include *WATER* in a specification with only *MEDIM* and per capita income, its estimated coefficient (not shown in Table 4) is 0.189 and significant. *WATER* always enters as a significant determinant of health outcomes when included along with medical imports and income. This suggests that *WATER* is collinear with other health inputs (the correlation between *WATER* and *CAL* and *PHYSICIANS* is 0.73 and 0.78, respectively), so that it loses its significance when these are included in the specification.[30]

The results in the second panel of Table 4 for imports of medical capital and equipment (*MCAPIM*) are very similar. It is interesting to note that *MCAPIM* has an even stronger positive (and statistically significant) impact on life expectancy than *MEDIM*, with elasticity estimates in the range 0.017-0.081 and statistically significant for all models. Moreover, the impact of *PHARD* on life expectancy remains positive and significant in models 2-5, as before, but its magnitude is smaller. In models (6) and (7) the estimate of *PHARD* is statistically insignificant. If *MCAPIM* embodies foreign R&D induced medical technologies to a greater degree than some of the other import categories included in the more aggregate measure, this should reduce the potential of attributing what is, in effect, embodied technology diffusion to direct flow of ideas as measured by the

[29]Specifically, the correlations betwen *MEDIM*, *MEDCAPIM*, and *PHAIM* and life expectancy are 0.65, 0.81 and 0.58 for the smaller sample compared to 0.71, 0.83 and 0.65 for the larger sample. Similarly with male mortality they are -0.64, -0.79 and -0.59 for the smaller sample compared to -0.73, -0.83, -0.68, for the larger sample. Finally, the correlations with infant mortality are -0.66, -0.80 and -0.59 for the smaller sample compared to -0.79, -0.88, and -0.74, for the larger sample.

[30]Another potentially important determinant of life expectancy is sanitation (defined as the percentage of the population with access to improved sanitation facilities). When we consider sanitation in a specification along with medical imports and income, its estimate is highly significant (elasticity is 0.121 and t-statistic = 3.20). However, when we include additional, potentially collinear, variables the impact of sanitation becomes statistically indistinguishable from zero with no gain in the adjusted R^2, much like *WATER*.

Table 6: Cross-country infant mortality regressions

Specif. 1	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MEDIM	−.2176*	−.2134*	−.2135*	−.1665*	−.1331*	−.0846**	−.0826**
	(−5.69)	(−5.99)	(−5.82)	(−3.51)	(−3.52)	(−2.43)	(−2.28)
INC	−.8511*	−.8705*	−.8708*	−.7814*	−.7502*	−.1838***	−.1765
	(−9.32)	(−9.17)	(−9.36)	(−5.85)	(−6.39)	(−1.68)	(−1.57)
PHARD	—	−.3092*	−.3092*	−.3109*	−.1119	.0145	.0170
		(−3.17)	(−3.15)	(−3.22)	(−0.97)	(0.12)	(0.14)
TROP	—	—	−.0006	−.0236	−.0659	−.0476	−.0482
			(−0.01)	(−0.52)	(−1.31)	(−1.45)	(−1.48)
CAL	—	—	—	−.9012	−.1567	−.0048	.0009
				(−1.51)	(−.25)	(−0.01)	(0.001)
PHYSI	—	—	—	—	−.1759*	−.0851	−.0814
					(−2.78)	(−1.30)	(−1.24)
ILLIT	—	—	—	—	—	.2645*	.2653*
						(6.05)	(6.06)
WATER	—	—	—	—	—	—	−.0259
							(−.29)
Adj. R^2	80.0	82.2	81.9	82.1	83.6	84.4	84.1
Obs.	72	72	72	70	70	59	59

Specif. 2	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MCAPIM	−.2704*	−.2535*	−.2579*	−.2214*	−.1779*	−.1008**	−.1009**
	(−7.99)	(−7.36)	(−6.98)	(−3.82)	(−3.48)	(−2.38)	(−2.11)
INC	−.6487*	−.6893*	−.6943*	−.6615*	−.6569*	−.1527	−.1528
	(−7.25)	(−7.48)	(−7.58)	(−5.34)	(−5.89)	(−1.49)	(−1.47)
PHARD	—	−.1589***	−.1562***	−.1783***	−.0324	.0660	.0659
		(−1.73)	(−1.68)	(−1.82)	(−0.27)	(0.55)	(0.55)
TROP	—	—	−.0182	−.0327	−.0652	−.0508	−.0508
			(−0.46)	(−0.74)	(−1.34)	(−1.55)	(−1.57)
CAL	—	—	—	−.5883	−.0489	.0899	.0898
				(−0.94)	(−0.07)	(0.18)	(0.17)
PHYSI	—	—	—	—	−.1478**	−.0827	−.0827
					(−2.41)	(−1.28)	(−1.27)
ILLIT	—	—	—	—	—	.2597*	.2597*
						(5.83)	(5.85)
WATER	—	—	—	—	—	—	.0004
							(0.005)
Adj. R^2	83.8	84.2	84.0	83.4	84.3	84.8	84.5
Obs.	73	73	73	71	71	60	60

Specif. 3	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
PHAIM	−.1819*	−.1879*	−.1872*	−.1417*	−.1139*	−.0704**	−.0689**
	(−4.49)	(−5.04)	(−4.89)	(−3.09)	(−3.30)	(−2.19)	(−2.06)
INC	−.9404*	−.9361*	−.9330*	−.8137*	−.7672*	−.2049***	−.2000***
	(−9.89)	(−9.68)	(−9.91)	(−6.07)	(−6.61)	(−1.92)	(−1.86)
PHARD	—	−.3509*	−.3508*	−.3402*	−.1231	.0039	.0057
		(−3.70)	(−3.69)	(−3.63)	(−1.06)	(0.03)	(0.05)
TROP	—	—	.0054	−.0178	−.0616	−.0478	−.0483
			(0.12)	(−0.39)	(−1.24)	(−1.47)	(−1.49)
CAL	—	—	—	−0.9895***	−.2015	−.0104	−.0052
				(−1.67)	(−0.32)	(−0.02)	(−0.01)
PHYSI	—	—	—	—	−.1814*	−.0934	−.0907
					(−2.88)	(−1.44)	(−1.39)
ILLIT	—	—	—	—	—	.2648*	.2652*
						(6.15)	(6.16)
WATER	—	—	—	—	—	—	−.0192
							(−0.22)
Adj. R^2	79.0	81.8	81.6	82.2	83.8	84.7	84.4
Obs.	73	73	73	71	71	60	60

Notes: * p-value <0.01, ** p-value<0.05, *** p value<0.10. Heteroskedasticity-consistent finite sample standard errors are used in constructing t-statistics.

R&D stock variable (*PHARD*). The results are similar, but somewhat weaker, in the third panel of Table 4 that utilizes pharmaceutical imports alone (*PHAIM*). Elasticities of life expectancy with respect to *PHAIM* range from 0.046 to a (marginally insignificant) low of 0.01 in model (5). At the same time, *PHARD* now plays a more important role with elasticities ranging from 0.175 to a (statistically insignificant) low of 0.039 in models (6) and (7).

The finding that imports of medical capital and equipment (*MCAPIM*) have a greater impact on health status than aggregate medical imports (*MEDIM*) suggests that our estimates do not merely capture a broad "trade openness" effect, but instead depend on the degree to which a given import type embodies R&D-induced technology. This conclusion is reinforced when we add a general measure of trade openness in the baseline specification (model 3). While estimates of medical imports always retain their economic and statistical significance, the estimates of general trade openness are always smaller than those for medical imports and are never statistically different from zero.[31] This conclusion remains unchanged irrespective of health status, openness, or medical imports measure used.

One potential explanation for the impact of medical imports on health would be that they serve as a proxy for the status of the domestic health sector. To address this issue, we include a measure of the number of hospital beds per thousand people as an indication of the status of the domestic health sector and to isolate the impact of technology flows. This variable is correlated with *MEDIM* (correlation coefficient = 0.79) and even more highly correlated with medical capital and equipment (0.84). When this variable is introduced in the baseline specification, its estimate is highly significant (elasticity is 0.075 and t-statistic = 3.07) but becomes statistically indistinguishable from zero when we include additional variables. More importantly, the positive impact of *MEDIM* (elasticity estimate is 0.029 and t-statistic = 2.09) and *PHARD* (elasticity estimate is 0.164 and t-statistic = 6.22) remains unaltered, suggesting that our two measures of technology flows operate independently of this measure of the domestic health sector. The results for the other two measures of medical imports, *MCAPIM* and *PHAIM*, including the hospital beds variable are

[31] We use the log of the number of years during which a country is open from Hall and Jones (1999) and the log of the Frankel and Romer (1999) predicted trade share computed from a gravity model based only on population and geography as general indicators of trade openness. The estimates are not reported in Table 4 but are available, upon request, and briefly summarized here. Using life expectancy as our measure of health status and *MEDIM* as the measure of medical imports, the estimated coefficient for opennness (Hall-Jones measure) is 0.016 (t-statistic = 1.13), while the estimate for *MEDIM* is 0.039 (t-statistic = 3.85) and for *PHARD* is .087 (t-statistic = 3.09). When we use the Frankel-Romer measure, the estimated coefficient for openness becomes -0.005 (t-statistic = -0.18), while the estimate for *MEDIM* is 0.052 (t-statistic = 3.04) and for *PHARD* 0.158 (t-statistic = 5.50).

very similar.

In Tables 5 and 6, we explore further the relation between imports of medical technology and health and measure health status by male mortality rates and infant mortality rates, respectively. Compared to the estimates for life expectancy, the results for mortality rates present both similarities and some interesting differences.

The first panel of Table 5 shows that the elasticity of male mortality with respect to *MEDIM* and *PHARD* is about twice that of the life expectancy elasticity. The estimates become (marginally) insignificant once we control for the number of physicians or female illiteracy. As mentioned previously, the number of physicians also captures in part the flow of ideas and thus acts to reduce the estimated impact of *PHARD*. Proximity to the tropics increases male mortality rates in model (3), but this effect loses significance when the number of physicians or female illiteracy is included. Calorie intake has a strong negative impact on male mortality rates with an elasticity of -1.192 in model (4). The elasticity of male mortality rates with respect to physicians, is also relatively high and robust across models. The (absolute) values of these elasticities are more than twice those for life expectancy. Illiteracy of young women has no statistically significant effect on male mortality. We suggest that the main impact of female illiteracy on health is through infant mortality (as will be discussed presently). Finally, the estimated elasticity of male mortality with respect to income per person ranges from -0.287 in model (2) to -0.059 and statistically insignificant in model (6).

In Table 6, we report estimates for infant mortality rates. In model (2) the (absolute) value of the elasticity of infant mortality rates with respect to *MEDIM* is about four times the life expectancy elasticity and about two times the male mortality elasticity. The estimated elasticity of infant mortality rates with respect to *PHARD* is -0.31 in models (2)-(4), but becomes insignificant once we introduce the number of physicians in model (5). Proximity to the tropics does not seem to have a significant impact on infant mortality rates, and neither does calorie intake. The elasticity of infant mortality rates with respect to physicians is -0.176. Illiteracy among young women has a significant effect on infant mortality rates and the highest elasticity amongst the explanatory variables in model (6): a 10 percent increase in female illiteracy is associated with a 2.7 percent increase in infant mortality. This result provides evidence and reinforces the oft-cited link between a mother's education and survival probabilities of infants. Amongst our three health indicators, increases in per capita income have the largest impact (in terms of elasticity) on infant mortality. We also note that, while per capita income is significant in all models, about 75 percent of its

Table 7: Instrumental Variables Estimation for Baseline Specification (Model 3)

	LIF/MED	LIF/MCAP	LIF/PHA	MAL/MED	MAL/MCAP	MAL/PHA	INF/MED	INF/MCAP	INF/PHA
IMP.	.0330***	.0373***	.0313**	−.1003*	−.0979*	−.0961*	−.1687*	−.1977*	−.1529*
	(1.93)	(1.81)	(1.96)	(−3.63)	(−3.44)	(−3.69)	(−2.91)	(−2.63)	(−2.97)
INC	.1695*	.1460*	.1785*	−.3249*	−.2740*	−.3394*	−1.0557*	−.9255*	−1.0822*
	(5.72)	(3.75)	(6.42)	(−5.35)	(−3.98)	(−5.95)	(−10.33)	(−6.79)	(−11.34)
PHARD	.1501*	.1263*	.1577*	−.2615*	−.1989*	−.2698*	−.2885*	−.1609	−.2969*
	(4.78)	(3.54)	(5.28)	(−3.71)	(−2.62)	(−4.08)	(−2.61)	(−1.28)	(−2.79)
TROP	−.0378*	−.0322*	−.0381*	.1484*	.1319*	.1512*	.0582	.0282	.0624
	(−2.74)	(−2.24)	(−2.68)	(4.65)	(3.85)	(4.73)	(0.92)	(0.45)	(0.97)
Adj. R^2	65.9	66.6	67.6	65.6	64.4	66.9	78.7	80.0	78.9
Obs.	64	64	65	62	62	63	64	64	65

Notes: * p-value <0.01, ** p-value<0.05, *** p value<0.10, Heteroskedasticity-consistent finite sample standard errors are used. The abbreviation LIF stands for LIFE, MAL for MALE, INF for INFANT, MED for MEDIM, MCAP for MCAPIM, and PHA for PHAIM.

impact goes away as soon as we control for female illiteracy rates.

4.3 Robustness analysis

We consider several variants of our results as robustness checks and also to provide additional insights into the health-medical technology diffusion relationship. First, we explore the possible endogeneity of medical imports by instrumenting for average medical imports by their initial level. Second, we consider the robustness of our results to different subsamples. Finally, we expand our data to consider panel estimation in order to take advantage of the time dimension in the data.

4.3.1 Instrumenting for medical imports

We estimate our baseline specification instrumenting average medical imports over the 1964-95 period by their predetermined value at the beginning of the period (1961-1963). We consider this because, in many cases, observations for 1961 (the initial year) are missing. The rationale is that the average value of medical imports per capita may be endogenous to health outcomes during the thirty-five year period. To the extent that future health status cannot cause the initial value of medical imports, we tackle this issue by using the 1961-63 average value of medical imports as a predetermined instrument for medical imports during 1964-95. We note that, while the most common practice for resolving the endogeneity problem has been the instrumental variables (IV) approach, in cross-country regressions treatment of endogeneity problems is less than satisfactory because of the lack of a set of viable exogenous instruments.[32] Bearing this in mind, in Table

[32]Durlauf (2001, p.66), among others, argues that studies using IV to address endogeneity are not convincing as their choice of instruments does not meet the necessary exogeneity requirements.

7 we present indicative IV results for our baseline specification with the three different measures of health status and three measures of medical imports. In the first three columns, we measure health status with life expectancy, in the following three columns with male mortality rates, and in the last three columns with infant mortality rates. The results reinforce our previous conclusions and suggest that real per capita medical imports have a positive causal impact on health status, irrespective of measure of medical imports or health status.

4.3.2 Endogenous subsample splitting

We follow Hansen's (2000) methodology that searches for endogenously determined subsamples in cross-country data in order to explore the possibility of a threshold in the underlying relationship. Hansen (2000) develops a statistical theory of threshold estimation in the linear regression context that allows for cross-section observations. The main advantage of Hansen's methodology over the regression-tree model (e.g. Durlauf and Johnson (1995)) is that it is based on an asymptotic distribution theory that can formally test the statistical significance of regimes selected by the data.[33]

We select model (5) in Tables 4-6 to investigate possible subsample splitting. The reason is twofold: first, it allows for a large number of observations *and* regressors; and, second, it is generally the model with the least pronounced effect of medical imports – our key explanatory variable – on health (see Tables 4-6). In particular, we search for endogenously determined subsamples using the three proxies for medical imports (*MEDIM*, *MCAPIM*, *PHAIM*) as potential threshold variables. The entire exercise involves nine variations of model (5) (three panels in each of Tables 4-6). To save space and because the results are qualitatively similar for the three measures of health status, we present results only with life expectancy as the depended variables (the remaining results are available from the authors upon request). That is, we consider three variations of model (5), with life expectancy as the dependent variable, in which *MEDIM*, *MCAPIM*, *PHAIM* are the regressors (and potential threshold variables), respectively. As an additional robustness check, we have applied this threshold methodology to model (6); the results are reported in Appendix Table A2.

[33]For a detailed discussion of the statistical theory for threshold estimation in linear regressions, see Hansen (2000) and Caner and Hansen (2004).

Table 8: List of countries in subsamples

Thresh.: MEDIM		**Thresh.: MCAPIM**		**Thresh.: PHAIM**	
Sub. 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)	*Sub.* 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)	*Sub.* 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)
Angola	Algeria	Angola	Algeria	Angola	Algeria
Argentina	Australia	Bangladesh	Argentina	Argentina	Australia
Bangladesh	Austria	Bolivia	Australia	Bangladesh	Austria
Bolivia	Canada	Cameroon	Austria	Bolivia	Cameroon
Brazil	Costa Rica	China	Brazil	Brazil	Canada
Cameroon	Cote D'Ivoire	Cote D'Ivoire	Canada	Chile	Costa Rica
Chile	Cyprus	Ethiopia	Chile	China	Cote D'Ivoire
China	Denmark	Ghana	Colombia	Colombia	Cyprus
Colombia	Ecuador	Haiti	Costa Rica	Egypt	Denmark
Egypt	Finland	India	Cyprus	El Salvador	Ecuador
El Salvador	Greece	Indonesia	Denmark	Ethiopia	Finland
Ethiopia	Iceland	Kenya	Ecuador	Ghana	Greece
Ghana	Iran	Madagascar	Egypt	Guatemala	Iceland
Guatemala	Ireland	Malawi	El Salvador	Haiti	Iran
Haiti	Israel	Mali	Finland	Honduras	Ireland
Honduras	Jamaica	Mozambique	Greece	India	Israel
India	Jordan	Myanmar	Guatemala	Indonesia	Jamaica
Indonesia	Korea	Nigeria	Honduras	Kenya	Jordan
Kenya	Mauritius	Pakistan	Iceland	Korea	Mauritius
Madagascar	New Zealand	Philippines	Iran	Madagascar	New Zealand
Malawi	Norway	Rwanda	Ireland	Malawi	Norway
Malaysia	Panama	Senegal	Israel	Malaysia	Panama
Mexico	Portugal	Sierra Leone	Jamaica	Mali	Portugal
Morocco	Spain	Sri Lanka	Jordan	Mexico	Spain
Mozambique	Tunisia	Sudan	Korea	Morocco	Tunisia
Myanmar	Uruguay	Tanzania	Malaysia	Mozambique	Uruguay
Nigeria	Venezuela	Uganda	Mauritius	Myanmar	Venezuela
Pakistan		Zaire	Mexico	Nigeria	
Paraguay		Zambia	Morocco	Pakistan	
Peru		Zimbabwe	New Zealand	Paraguay	
Philippines			Norway	Peru	
Rwanda			Panama	Philippines	
Senegal			Paraguay	Rwanda	
Sierra Leone			Peru	Senegal	
Sri Lanka			Portugal	Sierra Leone	
Sudan			Spain	Sri Lanka	
Tanzania			Thailand	Sudan	
Thailand			Tunisia	Tanzania	
Turkey			Turkey	Thailand	
Uganda			Uruguay	Turkey	
Zaire			Venezuela	Uganda	
Zambia				Zaire	
Zimbabwe				Zambia	
				Zimbabwe	
(43)	(27)	(30)	(41)	(44)	(27)

Table 9: Subsample regressions (Model 5)

	Thresh.: MEDIM		**Thresh.: MCAPIM**		**Thresh.: PHAIM**	
	Sub. 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)	*Sub.* 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)	*Sub.* 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)
IMPORTS	−.0024 (−.21)	.0187*** (1.82)	−.0087 (−.50)	.0458* (3.15)	−.0072 (−.68)	.0124[1] (1.42)
INC	.1101* (3.34)	.0228 (1.07)	.0853* (2.43)	.0399** (2.05)	.0998* (3.27)	.0241 (1.09)
PHARD	.1568* (3.27)	.05261*** (2.02)	.2224* (3.31)	.0150 (.73)	.1587* (3.42)	.0616** (2.21)
TROP	.0169** (1.98)	−.02869*** (−1.91)	.0188** (2.14)	.0141 (.99)	.0179** (2.11)	−.0325** (−2.22)
CAL	.2719** (2.27)	−.1425 (−1.18)	.4384** (2.13)	.0505 (.60)	.2778** (2.48)	−.1194 (−1.06)
PHYSI	.0505** (2.57)	.0920* (6.87)	.0545** (2.75)	.0333*** (1.87)	.0518* (2.80)	.0943* (8.35)
Adj. R^2	70.9	86.5	53.7	76.2	73.4	90.6
Obs.	43	27	30	41	44	27

Notes: Life expectancy is the dependent variable. * p-value <0.01, ** p-value<0.05, *** p value<0.10,
[1]p-value = 0.170. Heteroskedasticity-consistent finite sample standard errors are used in constructing t-statistics.

Hansen's statistical theory allows for one threshold for each threshold variable and we use the heteroskedasticity-consistent Lagrange Multiplier test developed by Hansen (1996). First, we consider model (5) with *MEDIM* as the regressor and potential threshold variable. The bootstrap Lagrange multiplier test statistic for an endogenous sample split is significant (p-value = 0.06), indicating that there exists a sample split based on *MEDIM*. The least-squares estimate of the threshold parameter is 1.79, so that *MEDIM* divides the sample of 70 countries into a low-imports group (below 1.79) with 43 countries and a high-imports group (above 1.79) with 27 countries. Second, we consider *MCAPIM* as a threshold variable. The bootstrap Lagrange multiplier test statistic is highly significant (p-value = 0.002) and the estimate of the threshold level is -0.72. *MCAPIM* splits the sample of 71 countries into two subsamples with 30 countries in the low-imports group and 41 countries in the high-imports group. Finally, *PHAIM* is considered as a threshold variable. The bootstrap Lagrange multiplier test statistic is also significant (p-value = 0.039) and the estimate of the threshold level is 1.42. Thus the sample can be split into two subsamples comprising of 44 countries (above 1.42) and 27 countries (below 1.42). Table 8 presents the countries in the three pairs of subsamples.

In Table 9, we present estimates of the regression coefficients of the three variants of model

(5) for the two identified regimes. The estimates for virtually all regressors vary extensively in magnitude and significance in each pair of subsamples. For example, *PHARD* has a much stronger impact for countries in the low-imports subgroup. More importantly, the subsample estimates reveal that the effect of medical imports on life expectancy is particularly pronounced in the subsample with high medical imports (Subsample 2), whereas in the subsamples with low medical imports (Subsample 1) the relationship is insignificant. With *MEDIM* as a threshold variable, the coefficient estimate for *MEDIM* is -0.002 and insignificant in Subsample 1, and 0.019 and significant (10% level) in Subsample 2. Similarly, with *MCAPIM* as a threshold variable, the estimate for *MCAPIM* is -0.009 and insignificant in Subsample 1, and 0.046 and highly significant (1% level) in Subsample 2. Finally, with *PHAIM* as a threshold variable, the relevant coefficient estimates are -0.007 and insignificant in Subsample 1, and 0.012 and marginally insignificant (17% level) in Subsample 2. To conclude, threshold estimation reveals another facet of the relationship between medical imports and health. It appears that countries have to surpass a threshold level of medical imports before they can reap the benefits of medical imports in terms of improved health. This conclusion holds irrespective of model: similar results for model (6) are reported in Appendix Table A2.

4.3.3 Panel estimation

The relation between health status and technological diffusion is a long-run one. For this reason, we have emphasized the cross-sectional dimension of the data. We also constructed a panel dataset to consider the robustness of the main findings to the time dimension. We divided our data sample into four subperiods corresponding to 1961-1969, 1970-1979, 1980-1989 and 1990-1995. The unconditional correlations for the panel are for the most part strikingly similar to the cross-sectional correlations in Table 3. For example, the correlations between medical imports and our three measures of health status are 0.66 (life expectancy), -0.76 (infant mortality), and -0.69 (male mortality). The same is true for the correlations between the three indicators of health status and each of our other two measures of imports. A notable exception is the correlation between health status and *PHARD*: they are much higher than in the cross section.[34] We report the unconditional panel correlations in Appendix Table A3.

Table 10 contains panel regression results. It includes three panels: one for each of three

[34]The panel correlations are 0.52, -0.50, and -0.45 for life expectancy, infant mortality, and male mortality respectively, compared to 0.31, -0.10, and -0.22 in the cross-section.

Table 10: Panel regressions

	LIFE/MEDIM			LIFE/MCAPIM			LIFE/PHAIM		
Specif.	Model 1	Model 4	Model 7	Model 1	Model 4	Model 7	Model 1	Model 4	Model 7
IMP.	.0494* (6.67)	.0221* (2.57)	.0123** (2.39)	.0703* (10.22)	.0336* (3.92)	.0148** (2.12)	.0411* (5.66)	.0188** (2.23)	.0127* (2.70)
INC	.1308* (8.05)	.0886* (5.17)	.0255** (2.07)	.0784* (5.10)	.0704* (3.84)	.0225*** (1.87)	.1444* (9.01)	.0908* (5.43)	.0252** (2.07)
PHARD	—	.1535* (10.11)	.0607* (3.52)	—	.1351* (9.16)	.0527* (3.14)	—	.1584* (10.20)	.0645* (3.74)
CAL	—	.4180* (7.34)	.1313* (2.60)	—	.3584* (6.29)	.1199** (2.33)	—	.4287* (7.58)	.1318* (2.64)
PHYSI	—	—	.0441* (4.88)	—	—	.0435* (4.64)	—	—	.0437* (4.89)
ILLIT	—	—	−.0316* (−4.79)	—	—	−.0308* (−4.57)	—	—	−.0316* (−4.85)
WATER	—	—	.0139 (.99)	—	—	.0127 (0.89)	—	—	.0131 (0.94)
Adj. R^2	59.4	74.8	84.2	67.2	75.9	84.2	57.3	74.4	84.3
Obs.	283	209	153	283	209	153	285	210	154

	MALE/MEDIM			MALE/MCAPIM			MALE/PHAIM		
Specif.	Model 1	Model 4	Model 7	Model 1	Model 4	Model 7	Model 1	Model 4	Model 7
IMP.	−.1299* (−7.47)	−.0549** (−2.31)	−.0227 (−1.06)	−.1692* (−10.73)	−.0829* (−3.39)	−.0314 (−1.27)	−.1119* (−6.34)	−.0469** (−2.04)	−.0234 (−1.19)
INC	−.2696* (−6.95)	−.2003** (−4.66)	−.0881** (−2.06)	−.1576* (−4.30)	−.1556* (−3.34)	−.0809*** (−1.92)	−.3004* (−7.81)	−.2042* (−4.96)	−.0822** (−1.97)
PHARD	—	−.2962* (−7.39)	−.0465 (−0.69)	—	−.2497* (−6.17)	−.0309 (−0.49)	—	−.3078** (−7.65)	−.0529 (−0.78)
CAL	—	−1.016* (−6.47)	−.2837 (−1.55)	—	−.8668* (−5.45)	−.2555 (−1.37)	—	−1.047* (−6.63)	−.2802 (−1.54)
PHYSI	—	—	−.1612* (−5.90)	—	—	−.1588* (−5.78)	—	—	−.1610* (−5.95)
ILLIT	—	—	.0336 (1.53)	—	—	.0315 (1.40)	—	—	.0343 (1.57)
WATER	—	—	−.0439 (−1.06)	—	—	−.0397 (−0.97)	—	—	.0529 (−0.78)
Adj. R^2	59.7	71.9	74.8	66.9	73.2	76.4	57.5	71.6	74.8
Obs.	267	199	144	267	199	144	269	200	145

	INFANT/MEDIM			INFANT/MCAPIM			INFANT/PHAIM		
Specif.	Model 1	Model 4	Model 7	Model 1	Model 4	Model 7	Model 1	Model 4	Model 7
IMP.	−.2746* (−9.83)	−.2139* (−5.75)	−.1238* (−5.29)	−.3301* (−14.05)	−.2745* (−7.23)	−.1369* (−4.43)	−.2405* (−8.49)	−.1859* (−4.93)	−.1131* (−5.33)
INC	−.6639* (−10.75)	−.5971* (−6.89)	−.0893 (−1.57)	−.4794* (−8.20)	−.4736* (−5.52)	−.0613 (−1.12)	−.7258* (−11.73)	−.6272* (−7.24)	−.0993*** (−1.77)
PHARD	—	−.3371* (−5.03)	−.0719 (−0.96)	—	−.1876* (−2.82)	.0081 (0.11)	—	−.3806* (−5.51)	−.0937 (−1.25)
CAL	—	−1.064* (−3.39)	−.2784 (−1.09)	—	−.7387** (−2.26)	−.1876 (−0.71)	—	−1.156* (−3.71)	−.3084 (−1.23)
PHYSI	—	—	−.0372 (−1.05)	—	—	−.0355 (−0.96)	—	—	−.0385 (−1.10)
ILLIT	—	—	.2918* (11.68)	—	—	.2863* (11.45)	—	—	.2929* (11.79)
WATER	—	—	.0132 (0.27)	—	—	.0193 (0.39)	—	—	.0078 (0.17)
Adj. R^2	77.6	80.7	85.2	81.8	82.2	84.8	75.8	79.9	85.2
Obs.	285	210	154	285	210	154	287	211	155

Notes: * p-value <0.01, ** p-value<0.05, *** p value<0.10. Heteroskedasticity-consistent finite sample standard errors used.

measures of health status. In order to conserve space, we report estimates for each of the three measures of medical imports for three specifications that correspond to cross-sectional specifications (1), (4) and (7). We consider all health inputs utilized in cross-sectional analysis, with the exception of tropical proximity because that measure is inherently cross-sectional.[35] As previously, in all models we control for income per capita via the exogenous component of income. We also control for the presence of global exogenous shocks specific to each decade by including decade-specific dummy variables (not shown in Table 10).

A look at the first panel of Table 10 shows that the estimated coefficients are very close to those of the cross sectional estimation. The results support both the 'embodied' medical technology diffusion hypothesis and the 'disembodied' technology diffusion hypothesis: the impact of medical imports and *PHARD* on life expectancy is positive and highly significant for all three specifications (1, 4, and 7) irrespective of measure of medical imports used. Additional health inputs such as calorie intake, physician availability, and female illiteracy are always significant determinants of life expectancy, as is income per capita. As in the cross-sectional analysis, access to water is insignificant when included along with other inputs (but significant when included only with medical imports and *PHARD*).

The estimates in the second panel of Table 10 for male mortality tell a similar story. The one exception is specification 7, where the estimated coefficients for medical imports and *PHARD* are negative but insignificant. Finally, the estimates for infant mortality rates in the third panel are supportive of the embodied technology diffusion hypothesis: the estimated coefficient for the impact of medical imports is statistically significant for all specifications irrespective of import measure. On the other hand, the coefficient estimate for *PHARD* is consistent with the disembodied technology diffusion hypothesis for specification 4 but not for 7. Finally, female education has the largest impact (in terms of elasticity) on infant mortality and is also highly significant.

5 Conclusion

While much has been written about the beneficial effects of international R&D spillovers from capital goods technology for both developed and developing economies, there has been no research on potential benefits from the diffusion of medical technology. Our main hypothesis is that medical

[35]Including it leaves other estimated coefficients virtually unchanged, while *TROP* itself is usually insignificant. Moreover, the adjusted R^2 with *TROP* included is usually lower.

technologies resulting from R&D in advanced economies benefit not only the countries originating these technologies, but also other nations, in terms of enhanced health status. The extent of these benefits is captured by direct imports of goods embodying these technologies or in terms of ideas flowing from the originators of R&D to the rest of the world. Moreover, these benefits depend on the intensity of medical goods trade by each recipient nation, in the first instance, and, second, by the size of medical R&D expenditures in the source countries with which a recipient trades.

In this paper, we present a simple model of medical technology imports where individuals can influence their probability of survival by the amount of spending on imported medical goods. We test this model for a cross section of 73 economies that are not producers of medical technology or goods, but instead rely heavily (if not exclusively) on imports of medical technology. In our regression specifications we introduce a number of additional health inputs to ascertain the importance of medical imports, independent of these inputs. Our main message is that imports of medical goods are a significant determinant of health status in non-R&D performing economies. We also find strong evidence for the hypothesis that R&D diffuses from the originator nations to recipients in a disembodied form via the flow of ideas. While per capita income is a significant determinant of health status in some specifications, its importance goes away when additional health inputs are included. On the other hand the diffusion of medical technology is a consistent and significant contributor to health improvements in non-medical frontier economies in all specifications.

Along with other favorable domestic improvements, medical technology diffusion is in large part responsible for the decline in global inequality in life expectancy, especially during the latter half of the 20th century, as noted in the introduction. In recent years, governmental and non-governmental bodies have called for additional resources to be devoted to medical R&D, especially R&D directed at controlling communicable diseases pertinent to poorer nations (Type III diseases), and have highlighted the health and macroeconomic benefits of such resources (see the Commission on Macroeconomics and Health, 2001). Our evidence lends support to the benefits that such R&D investments would have on health outcomes in less advanced economies, as the fruits of such investments filter to the rest of the world through the diffusion of medical technology.

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Appendix

Table A1: Mean Values of Cross Section Data (73 Countries)

Country	**Code**	**Life Exp.**	**Male Mort.**	**Infant Mort.**	**Med. Imp.**	**Med.Cap. Imp.**	**Pharm. Imp.**
Algeria	DZA	4.064	5.541	4.648	2.509	0.290	2.318
Angola	AGO	3.691	6.316	5.086	1.151	-1.099	0.918
Argentina	ARG	4.231	5.325	3.679	1.729	0.358	1.221
Australia	AUS	4.301	5.158	2.569	3.468	2.186	2.862
Austria	AUT	4.285	5.249	2.876	4.383	2.767	3.898
Bangladesh	BGD	3.871	6.069	4.793	-0.857	-3.130	-1.200
Bolivia	BOL	3.930	5.971	4.819	0.879	-0.721	0.455
Brazil	BRA	4.116	5.478	4.311	0.891	-0.369	0.301
Cameroon	CMR	3.872	6.247	4.711	1.700	-1.152	1.422
Canada	CAN	4.315	5.073	2.623	3.676	2.614	2.794
Chile	CHL	4.202	5.535	3.679	1.772	0.596	1.058
China	CHN	4.145	5.772	4.142	-1.655	-2.548	-2.963
Colombia	COL	4.157	5.541	4.003	1.198	-0.204	0.622
Costa Rica	CRI	4.253	5.174	3.584	2.552	0.975	1.949
C. d'Ivoire	CIV	3.839	6.160	4.795	2.044	-0.931	1.849
Cyprus	CYP	4.297	5.036	2.920	3.608	1.583	3.212
Denmark	DEN	4.305	5.041	2.408	4.291	2.613	3.800
Ecuador	ECU	4.118	5.503	4.380	1.903	0.171	1.447
Egypt	EGY	4.010	5.597	4.820	1.438	-0.409	0.815
El Salvador	SLV	4.076	5.796	4.448	1.794	-0.019	1.287
Ethiopia	ETH	3.723	6.162	5.009	-0.702	-2.616	-1.206
Finland	FIN	4.286	5.418	2.192	3.836	2.309	3.387
Ghana	GHA	3.953	6.057	4.574	1.078	-1.277	0.796
Greece	GRC	4.308	4.970	3.064	3.375	1.507	2.981
Guatemala	GTM	4.014	6.036	4.459	1.736	-0.442	1.076
Haiti	HTI	3.900	5.971	4.866	0.559	-1.820	0.214
Honduras	HND	4.048	5.753	4.424	1.607	-0.364	1.171
Iceland	ICE	4.333	4.942	2.285	4.026	2.377	3.587
India	IND	3.968	5.721	4.691	-1.688	-2.712	-2.384
Indonesia	IDN	3.969	6.068	4.569	-0.519	-2.096	-1.085
Iran	IRN	4.044	5.339	4.649	2.041	0.136	1.574
Iraq	IRQ	4.059	5.623	4.554	2.179	0.327	1.808
Ireland	IRL	4.288	5.113	2.717	4.615	2.856	4.240
Israel	ISR	4.290	4.941	2.895	3.573	2.334	2.912
Jamaica	JAM	4.247	5.286	3.686	2.115	0.222	1.734
Jordan	JOR	4.213	5.322	3.751	2.855	1.109	2.465
Kenya	KEN	3.958	6.102	4.466	0.857	-1.439	0.515

Table A1: Mean Values of Cross Section Data (73 Countries) cont.

Country	**Code**	**Life Exp.**	**Male Mort.**	**Infant Mort.**	**Med. Imp.**	**Med. Cap. Imp.**	**Pharm. Imp.**
Korea	KOR	4.159	5.761	3.571	1.864	0.894	0.958
Madagascar	MDG	3.877	5.937	4.890	0.796	-1.917	0.505
Malawi	MWI	3.742	6.168	5.127	-0.475	-2.216	-0.965
Malaysia	MYS	4.185	5.659	3.577	1.677	0.243	1.060
Mali	MLI	3.710	6.222	5.165	—	-1.722	0.305
Mauritius	MUS	4.176	5.565	3.699	2.471	0.267	2.060
Mexico	MEX	4.177	5.476	4.080	1.551	0.478	0.853
Moroco	MAR	4.669	5.701	4.030	1.299	-0.649	0.918
Mozambique	MOZ	3.746	6.203	5.071	0.136	-2.376	-0.307
Myanmar	MMR	3.920	5.951	4.768	-0.838	-2.988	-1.295
New Zealand	NZL	4.291	5.190	2.643	3.418	1.749	3.027
Nigeria	NGA	3.808	6.289	4.791	0.796	-1.541	0.485
Norway	NOR	4.325	4.998	2.347	4.037	2.516	3.559
Pakistan	PAK	3.971	5.764	4.873	0.393	-1.673	-0.097
Panama	PAN	4.222	5.319	3.680	4.175	1.597	4.013
Paraguay	PRY	4.197	5.343	3.873	1.246	-0.216	0.418
Peru	PER	4.066	5.759	4.480	1.330	-0.515	0.958
Philippines	PHI	4.101	5.874	4.210	0.624	-1.249	0.210
Portugal	PRT	4.259	5.197	3.563	3.151	1.170	2.849
Rwanda	RWA	3.773	6.236	4.909	-0.033	-1.726	-0.401
Senegal	SEN	3.789	6.357	4.781	1.658	-1.015	1.420
Sierra Leone	SLE	3.544	6.345	5.274	0.731	-1.626	0.476
Singapore	SGP	4.257	5.387	2.699	4.198	2.866	3.286
Spain	ESP	4.310	5.069	2.966	2.958	1.541	2.395
Sri Lanka	LKA	4.197	5.292	3.644	0.238	-1.712	-0.222
Sudan	SDN	3.840	6.289	4.837	1.179	-2.054	0.379
Tanzania	TZA	3.856	6.221	4.796	0.207	-2.213	-0.196
Thailand	THA	4.124	5.712	4.048	1.157	-0.451	0.653
Tunisia	TUN	4.124	5.543	4.383	2.433	0.351	2.198
Turkey	TUR	4.093	—	4.656	1.231	-0.145	0.564
Uganda	UGA	3.862	6.207	4.726	-0.265	-2.214	-0.734
Uruguay	URY	4.252	5.197	3.575	2.079	0.460	1.606
Venezuela	VEN	4.206	5.429	3.753	2.315	0.965	1.773
Zaire	ZAR	3.856	—	4.777	-0.485	-2.858	-0.726
Zambia	ZMB	3.858	6.249	4.680	1.016	-0.844	0.656
Zimbabwe	ZWE	3.954	6.072	4.394	0.473	-1.092	-0.083

Notes: All variables are in logarithms. The sources are the World Development Indicators (WDI), and the OECD International Trade by Commodity (ITCS) databases. Summary statistics for the remainder of the data used in this paper are available from the authors.

Table A2: Subsample regressions (Model 6)

	Thresh.: MEDIM		**Thresh.: MCAPIM**		**Thresh.: PHAIM**	
	Sub. 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)	*Sub.* 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)	*Sub.* 1 (*Low Imp.*)	*Sub.* 2 (*High Imp.*)
IMPORTS	−.0007 (−0.08)	.0414* (3.03)	.0041 (0.29)	.0647* (3.91)	.0067 (0.68)	.0437* (3.54)
INC	.0352 (1.15)	.0625 (1.57)	.0258 (1.05)	.0243 (0.75)	−.0117 (−0.48)	.1484* (3.59)
PHARD	.0415 (0.85)	.0545 (0.96)	.0549 (1.34)	.0234 (0.66)	−.0112 (−0.23)	.1044* (3.11)
TROP	.0061 (0.92)	−.0282 (−1.65)	.0158* (2.84)	.0130 (0.93)	.0212** (2.47)	−.0091 (−0.73)
CAL	.1860 (1.47)	−.1489 (−0.89)	−.0875 (−0.65)	.1581*** (1.76)	−.3557*** (−1.96)	−.0256 (−0.21)
PHYSI	.0475* (2.76)	.0666** (2.19)	.0766* (5.57)	−.0067 (−0.27)	.1064* (6.18)	.0534** (2.47)
ILLIT	−.0744* (−3.99)	.0125 (−0.79)	−.0800* (−3.58)	−.0243 (−1.65)	−.0935* (−4.23)	.0057 (−0.44)
Adj. R^2	83.3	80.6	84.5	77.1	91.4	86.5
Obs.	37	22	27	33	21	39

Notes: Life expectancy is the dependent variable. * p-value <0.01, ** p-value<0.05, *** p value<0.10. Heteroskedasticity-consistent finite sample standard errors are used in constructing t-statistics.

Table A3: Unconditional panel correlations

	MEDIM	MCAPIM	PHAIM	PHARD	TROP	CAL	PHYSI	ILLIT	WATER	LIFE	INFANT	MALE	INC
MEDIM	1												
MCAPIM	0.94	1											
PHAIM	0.99	0.89	1										
PHARD	0.12	0.36	0.06	1									
TROP	-0.43	-0.46	-0.40	-0.05	1								
CAL	0.73	0.80	0.68	0.19	-0.51	1							
PHYSI	0.67	0.79	0.61	0.49	-0.55	0.76	1						
ILLIT	-0.56	-0.72	-0.49	-0.47	0.27	-0.63	-0.72	1					
WATER	0.59	0.70	0.56	0.46	-0.42	0.64	0.69	-0.54	1				
LIFE	0.66	0.80	0.59	0.52	-0.46	0.77	0.88	-0.80	0.72	1			
INFANT	-0.76	-0.87	-0.70	-0.50	0.45	-0.81	-0.81	0.89	-0.68	-0.88	1		
MALE	-0.69	-0.80	-0.63	-0.45	0.53	-0.77	-0.88	0.73	-0.69	-0.92	0.85	1	
INC	0.59	0.66	0.56	0.05	-0.44	0.71	0.64	-0.59	0.69	0.66	-0.75	-0.64	1

Notes: All variables are in natural logarithms. Complete data is available for 68 countries (except for ILLIT) and four sub-periods: 1961-1969, 1970-1979, 1980-1989 and 1990-1995. For the definition of variables see Table 3.

Derivation of Euler equations and steady-state conditions

Rewrite the household maximization problem substituting the state variables q_{t+1} and a_{t+1} (given by (3) and (4), respectively) in equation (2) to arrive at:

$$\max_{\left\{c_t,\{h_{jt}\}_{j=1}^{M_t}\right\}} \left\{ u(c_t) + \rho B \sum_{j=1}^{M_t} \frac{h_{jt}^{\gamma}}{v_t} V\left(w_t + (1+r_t)a_t - c_t - \sum_{j=1}^{M_t} p_{jt}h_{jt} \right) \right\}. \tag{A1}$$

The first order conditions (FOCs) are

$$\frac{\partial V(a_t)}{\partial c_t} = 0; \;\; u'(c_t) - \rho q_{t+1} V'(a_{t+1}) = 0 \tag{A2}$$

$$\frac{\partial V(a_t)}{\partial h_{jt}} = 0; \;\; q'_{t+1}(h_{jt})\rho V(a_{t+1}) - \rho q_{t+1} V'(a_{t+1}) p_{jt} = 0, \tag{A3}$$

where $q'_{t+1}(h_{jt}) = \frac{\partial q_{t+1}}{\partial h_{jt}}$. In addition,

$$V'(a_t) = \rho q_{t+1} V'(a_{t+1})(1+r_t). \tag{A4}$$

Combining (A2) and (A4) and iterating one period ahead yields equation (6) in the text:

$$u'(c_t) = \rho q_{t+1}(1+r_{t+1})u'(c_{t+1}). \tag{18}$$

Also combining (A2) and (A3) gives equation (7) in the text:

$$q'_{t+1}(h_{jt})\rho V(a_{t+1}) = \frac{B\gamma h_{jt}^{\gamma-1}}{v_t} \rho V(a_{t+1}) = p_{jt}\, u'(c_t). \tag{19}$$

Using the recursive structure of $V(a_t)$, we can rewrite the optimization problem as

$$V(a_{t+1}) = u(c_{t+1}) + \rho q_{t+2} V(a_{t+2}), \tag{A5}$$

and combining it with equation (7) yields

$$\frac{p_{jt}\, u'(c_t)}{\rho q'_{t+1}(h_{jt})} = u(c_{t+1}) + \rho q_{t+2} \frac{p_{jt+1}\, u'(c_{t+1})}{\rho q'_{t+2}(h_{jt+1})}. \tag{A6}$$

Then using the FOC (6) in the text yields the Euler equation (8)

$$(1+r_{t+1})\frac{q_{t+1}}{q'_{t+1}(h_{jt})} = \frac{1}{p_{jt}} \frac{u(c_{t+1})}{u'(c_{t+1})} + \frac{p_{jt+1}}{p_{jt}} \frac{q_{t+2}}{q'_{t+2}(h_{jt+1})}. \tag{20}$$

Equation (8) can be rewritten after substituting for the values of q and q' as

$$(1+r_t)M_t h_{jt} = \frac{\gamma}{p_{jt}} \frac{u(c_{t+1})}{u'(c_{t+1})} + M_{t+1} h_{jt+1} \frac{p_{jt+1}}{p_{jt}}. \tag{A7}$$

Next, we discuss the determination of prices p_{jt}. Given no production of new medical technologies in the domestic economy (we assume the countries of interest only import medical goods) the price is exogenously given and can be normalized to unity. Alternatively, we can add more structure

to the model by assuming that innovating firms abroad operate under monopolistic competition and choose monopoly prices, p_{jt}, according to the profit maximization problem

$$\max_{h_{jt}} \pi_{jt} = p_{jt}h_{jt} - h_{jt}, \tag{A8}$$

where, for simplicity, it is assumed that health goods are produced with the same production technology as consumption goods. The first order condition is

$$\frac{\partial \pi_{jt}}{\partial h_{jt}} = 0; \;\; p'_{jt}h_{jt} + p_{jt} - 1 = 0, \tag{A9}$$

or

$$p_{jt} = \frac{1}{1 + p'_{jt}\frac{h_{jt}}{p_{jt}}}. \tag{A10}$$

We can rewrite (7) in the text as:

$$p_{jt} = \frac{V\left(a_{t+1}\right)}{u'(c_t)} \frac{\rho B \gamma h_{jt}^{\gamma-1}}{v_t}, \tag{A11}$$

Taking the first derivative of p_{jt} with respect to h_{jt}, multiplying by $\frac{h_{jt}}{p_{jt}}$, and manipulating yields:

$$p'_{jt}\frac{h_{jt}}{p_{jt}} = \gamma - 1. \tag{A12}$$

Substituting (A12) into (A10) gives

$$p_{jt} = p = \frac{1}{\gamma}. \tag{A13}$$

This result implies symmetry in the model which in turn implies that $\sum_{j=1}^{M_t} p_{jt}h_{jt} = M_t p h_t$.

Next, we assert that the steady state assumption, $g_v = g_M^* = g_A$, is an assumption necessary for the existence of a balanced growth and one that secures that the probability of survival q is constant in steady state: this is the only logical assumption because q can not possibly grow indefinitely. To see why this assumption is important, consider the law of motion of q given in equation (4) which, after imposing the symmetry condition, can be written as

$$q_{t+1} = B\frac{M_t h_t^{\gamma}}{v_t}. \tag{A14}$$

Dividing by q_t and using the fact that, at the steady state, $g_h^* = 0$ and $g_y^* = g_c^* = g_k^* = g_M^* = g_A$, yields[36]

$$g_q^* + 1 = \frac{g_M^* + 1}{g_v^* + 1}. \tag{A15}$$

Therefore $g_q^* = 0$ (i.e. q is a constant) only when $g_v = g_M^*$.

[36]The steady-state growth conditions are derived by applying standard growth accounting methodology to equations (S3-S8).

Finally, we derive the steady-state level equations (13-15 in the text). Using the FOC (6) and the CRRA utility function $u(c_t) = c_t^{1-\sigma}/c_t$ gives

$$\begin{aligned} \frac{c_{t+1}}{c_t} &= \rho q_{t+1}(1+r_{t+1}) \\ 1+g_c &= \rho q_{t+1}(1+r_{t+1}), \end{aligned} \tag{A16}$$

which at the steady state yields equation (13).

Now substituting equation (A13) into equation (A7) and manipulating gives

$$(1+r_t)\frac{M_t}{M_{t+1}}\frac{M_{t+1}}{c_{t+1}}h_{jt} = \frac{\gamma^2}{1-\sigma} + \frac{M_{t+1}}{c_{t+1}}h_{jt+1}. \tag{A17}$$

At the steady state it becomes

$$\frac{1+r^*}{1+g_M^*}\frac{M^*}{c^*}h^* = \frac{\gamma^2}{1-\sigma} + \frac{M^*}{c^*}h^* \tag{A18}$$

and rearranging gives equation (14) in the text.

Finally, using equation (1) with the symmetry condition we readily obtain steady-state equation (15) in the text.