International Medical R&D Spillovers*

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Comments Welcome

Abstract

Does medical technology developed in countries close to the technology frontier have a significant impact on health and income in countries distant from this frontier? This paper considers a framework where lagging countries benefit from imports of embodied medical technology or from the flow of ideas resulting from research and development done by countries at the frontier. Using a cross-section of 73 importing countries, we show that medical technology diffusion is an important contributor to improved health measured by life expectancy, male mortality and infant mortality rates.

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

JEL Classification: O30, O40

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1 Introduction

Is medical technology diffusion from countries performing Research and Development (R&D) important for health and income outcomes in non-R&D performing economies? A large body of literature has studied 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. No study has considered the diffusion of medical technology across the world. 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.[1] In this paper, we propose that similar to capital goods used in manufacturing, medical goods such us pharmaceuticals or medical equipment used in the medical sector, 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 an affirmative answer to the question posed at the beginning of this paragraph, namely that advances in medical technology occur in a small group of developed economies and diffuse to the rest of the world either embodied in medical exports or "disembodied" in the form of flow of ideas.

Spending on R&D has been shown to boost productivity and economic growth not only in the economies of countries carrying out the R&D but also in foreign economies benefitting from international R&D spillovers. There is a lengthy literature documenting the importance of international R&D spillovers focusing exclusively on capital goods (see, e.g. Coe and Helpman (1995), Coe et al. (1997), Keller (2002), and Savvides and Zachariadis (2003.) No one study, however, focuses on potential welfare-enhancing benefits of medical R&D in technologically-advanced countries, in terms of health and productivity in less advanced countries. We aim to fill this gap by exploring how medically-related imports, including pharmaceuticals (e.g. vaccines and antibiotics) and medical equipment (e.g. surgical instruments) from countries with advanced medical technologies impact the health status in countries distant from the technology frontier.

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." Fogel (1994, p. 388) points to a potential explanation for the acceleration of life expectancy improvements when he points to "... the huge social investments made between 1870 and 1930,

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

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." In this paper, we argue that R&D-induced advances in medical technology in frontier countries systematically diffuse across the world and are thus partly responsible for the considerable drop in world life expectancy inequality observed during the twentieth century. Specifically, we examine the relation between medical R&D in ten technologically advanced countries and health and economic outcomes in the rest of the world. These countries benefit from foreign medical R&D even in the absence of domestic medical R&D and the extent of these beneficial effects should depend, among other things, on medical imports. In fact, if, similar to Caselli and Wilson (2002) and as shown by Eaton and Kortum (2001) in the case of 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, then these imports can sufficiently capture the impact on the overall health level in these countries. Alternatively, R&D carried out in advanced economies may have direct spillover effects in terms of generating knowledge and ideas that can be used (in the case of capital goods) by producers other than those carrying out the R&D. These producers may be located within the borders of the country or across the border. This direct effect 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.

Our main hypothesis relates to the work of Kremer (2002, page 67) who argues about the importance of modern medical technologies in allowing "tremendous improvements in health even at low income levels."[2] Here, we will empirically assess this supposition by studying the role of technology diffusion in determining health status, controlling for income levels and a variety of health inputs. Our baseline model links health outcomes to medical technology flows embodied in imports or directly via ideas. In our empirical analysis, we augment our baseline model to test the robustness of the relationship between medical technology flows and health outcomes. 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

[2]Kremer (2002, page 67) offers a convincing example supportive of the technology diffusion story, regarding life expectancy in Vietnam "of 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."

capita income and life expectancy in our data is 0.77). Our empirical strategy takes account of this interconnection, first, by including 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. Thus, we consider calorie intake per person, the number of physicians per thousand persons, female illiteracy rates, and access to an improved water source. 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 rate of disease arrival in the theoretical model described in the next section.

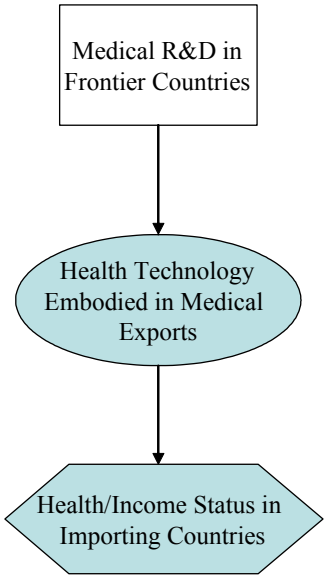
The remainder of the paper is organized as follows. Section 2 describes a simple theoretical model that links medical imports and endogenous life expectancy and serves to motivate our empirical analysis. Section 3 discusses our novel dataset on medical imports and takes a first look at the correlations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

2 A simple model of endogenous health

In this section we provide a theoretical justification for our main hypothesis relating medical imports to health and income. We construct a simple model in which the medical imports-health relationship emerges as an equilibrium outcome from optimal decisions by a representative agent. The novel feature of the model is that health is determined endogenously, whereas in most existing models it is exogenously given. We consider this unsatisfactory because the consumption of medical products has substantially contributed to increased longevity (see e.g. Easterly 1996, Lichtenberg 2002), and this consumption is the agents' decision.

Figure 1 summarizes our hypothesis regarding medical technology diffusion. R&D in advanced countries creates medical technology which then diffuses to other countries and impacts health status in two ways: either embodied in medical exports to those countries or through the direct transfer of knowledge and ideas. R&D expenditure in advanced countries' pharmaceutical and other health-related industries serve to enhance the technology content of specific medical products which can then imported by less advanced countries. These products improve the health status of the workforce, as documented by Shaw, Horrace, and Vogel (2002) for developed economies. Alternatively, medical R&D in advanced countries diffuses via the flow of ideas to less advanced

Figure 1: Illustration of baseline theoretical relationship



economies and translating in improved health of the recipients' population.

In what follows, we present a model of health-products consumption and endogenous life expectancy**.** To keep the model as simple as possible, we assume no domestic production of medical products or domestic medical R&D. Domestic agents take the frontier level of medical technology as given, and choose between medical products that will enhance their life expectancy (and their future utility) and consumption goods that enhance their utility instantaneously. This trade-off between health and consumption goods (and therefore future vs. present consumption) is the main innovation of the model.

2.1 Economic environment

The economy is populated by a constant number of identical agents. A representative agent has a finite life expectancy with probability q_t of being alive at period t. The probability of survival is endogenous and depends on individual consumption decisions of health products. Formally we assume that

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

where B is an exogenous parameter (reflecting e.g. genes, habits, geography), 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 consumption and g_v is the exogenous arrival of new illnesses and virus mutations that reduce the probability of survival. When an agent dies, she is immediately replaced by a new born that inherits all assets (a_t) accumulated by the deceased. For simplicity, we assume that the size of the population is constant over time and we normalize it to unity.

2.2 Household problem

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

$$V(a_t) = \max_{\{c_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \rho^t \left(\prod_{j=1}^{t} q_j \right) u(c_t) = \max_{\{c_t\}} \{u(c_t) + \rho q_{t+1} V(a_{t+1})\} \tag{1}$$

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

$$q_{t+1} = \gamma_1 \sum_{j=0}^{M_t} h_{jt}^{\gamma_2} (1 + g_v)^{-t}$$

$$\text{where } \{a_t, w_t, M_t, p_{jt}\}_{t=0}^{\infty} \text{ are given.}$$

V 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.

Optimality implies the following first-order conditions:

$$u'(c_t) = \rho q_{t+1} (1 + r_{t+1}) u'(c_{t+1}) \tag{2}$$

$$\frac{\partial q_{t+1}}{\partial h_{jt}} V(a_{t+1}) = \frac{\rho B \gamma h_{jt}^{\gamma-1}}{(1 + g_v)^t} V(a_{t+1}) = p_{jt}\, u'(c_t). \tag{3}$$

Using equations (1) and (3) yields the Euler equation

$$(1 + r_{t+1}) \left(\frac{q_{t+1}}{q_{t+1}^{(j)}} \right) = \frac{1}{p_{jt}} \left(\frac{u(c_{t+1})}{u'(c_t)} \right) + \frac{p_{jt+1}}{p_{jt}} \left(\frac{q_{t+1}}{q_{t+2}^{(j)}} \right), \tag{4}$$

where $q_{t+1}^{(j)}$ is the first derivative of q_{t+1} with respect to h_{jt-1}. Notice that the only difference between Euler equation (4) and the standard neoclassical Euler equation is the appearance of the probability of survival (q). Put differently, if we set $q = 1$ (the assumption made in the neoclassical model) then equation (4) is reduced to the standard Euler equation.

2.3 Consumption good production medical R&D

In our model, the only good that provides utility to consumers is manufactured with a Cobb-Douglas intensive production technology (given that $L_t = 1$)

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

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 competivive market it is straight forward to show that wages and rents are given respectively by

$$\begin{aligned} w_t &= (1-\alpha) y_t \\ r_t &= \alpha \frac{y_t}{k_t} - \delta. \end{aligned}$$

Since we are only interested in the experiences of those countries that import medical goods, we do not model medical R&D production that takes place in a few industrialized countries.[3]

2.4 Characterization of the aggregate economy

We are now ready to study the aggregate economy that is characterized by the following system of seven equations (S1-S7):

$$u'(c_t) = \rho q_{t+1}(1 + r_{t+1}) u'(c_{t+1}) \quad \text{(S1)}$$

$$\frac{\partial q_{t+1}}{\partial h_{jt}} V(a_{t+1}) = \frac{\rho B \gamma h_{jt}^{\gamma-1}}{(1+g_v)^t} V q_{t+1}; a_t = k_t \quad \text{(S2)}$$

$$q_{t+1} = B \sum_{j=1}^{M_t} h_{jt}^{\gamma} (1+g_v)^{-t} \quad \text{(S3)}$$

$$Y_t = k_t^{\alpha} A_t^{1-\alpha} \quad \text{(S4)}$$

$$i_t = k_{t+1} - k_t(1-\delta) \quad \text{(S5)}$$

$$y_t = c_t + i_t + M_t h_t; \quad \text{(S6)}$$

$$w_t = (1-\alpha) y_t; r_t = \alpha \frac{y_t}{k_t} - \delta, \quad \text{(S7)}$$

where δ is capital depreciation rate. Equations (S1)-(S2) are the two first-order conditions obtained from the household optimization problem. Equation (S3) is the survival probability equation, (S4)

[3]Modeling medical R&D production can be done by allowing a law of motion for health products (M_j). Even though interesting it is beyond the scope of this paper and is left for future research.

is the aggregate production function and (S5) is the law of motion of capital. Equation (S6) is the expenditure equation where, in addition to consumption and physical capital, agents spend part of their income on medical products ($M_t h_t$). Finally, equation (S7) shows input prices determined by competitive conditions.

2.5 Steady-state

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

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

and the Euler equation for health products as

$$\frac{c_t^*}{M_t^*} = \frac{1-\sigma}{\gamma^2} \left(\frac{r^* - g_A}{1 + g_A} \right) h^*,$$

where σ is the inverse of the intertemporal elasticity of substitution, * denotes the steady state, and $^-$ denotes a constant value. The probability of survival can then be derived as

$$q^* = \frac{BM^* (h^*)^\gamma}{1 + g_v}. \tag{5}$$

Equation (5) shows that in the steady state, the probability of survival, q, is positively related to the consumption of imported medical products, Mh^γ (the product of the variety times the amount of medical products scaled by the parameter γ_2). In addition, the probability of survival is shown to be negatively related to the rate of virus growth rate which is consistent with evidence. Equation (5) establishes the relationship between medical imports and health status and motivates the empirical investigation of the next section.[4]

3 Data description

In this section, we describe the data set we have assembled to test our main hypotheses. Subsequently, we take a first look at the relationship between imports and health with simple scatter plots. We focus on three different measures of health status: life expectancy, male mortality and infant mortality.

[4] An appendix that shows the algebraic derivation of the all equations in the model is available from the authors upon request.

We employ three main sources of data. First, the OECD International Trade by Commodity database (ITCS) contains medical-related exports (in thousand current $US) from each of Belgium, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the U.K., and the U.S. from 1961 to 2001. Initially, we consider the sum of the following pharmaceutical, medical, and health-related categories of imports from *SITC Revision 2*.

Table 1: Categories of imported medical products used in estimation

Medical & Pharmaceutical Products	Electric Apparatus for Medical Purposes
Medical Instruments & Appliances	Optical Goods
Insecticides, Hyg. & Pharm. Articles of Rubber	Laboratory, Hyg. & Pharm. Glassware
Medical, Dental, Surg. or Vet. Furniture	Orthopaedic Appl., Surg. Belts & the like

Notes: Medical and Pharmaceutical Products include, among other things, the following categories: Antibiotics, Antisera and Microbial Vaccines, and Medicaments Containing Antibiotics and Derivatives Thereof. For more information on medical product categories see the Appendix.

We also consider separately the sum of two categories as a measure of medical capital and equipment: Electric Apparatus for Medical Purposes and Medical Instruments & Appliances. We use Manufacturing sector and Chemicals industry price deflators from the 1998 OECD Intersectoral Database (ISDB 1998) to deflate imports in current dollars into constant 1990 $US. We construct a measure of real medical imports per capita by deflating imports in current dollars by the appropriate price deflator and by dividing by total population in thousands.[5]

Second, we use the *ANBERD* 2001 database for pharmaceutical R&D in eight technologically advanced countries (France, Germany, Italy, Japan, the Netherlands, Sweden, U.K., and U.S.) from 1973 to 1997. Specifically, we use the R&D expenditures in current PPP dollars series for the SIC Revision 2 category "Drugs and Medicines".[6] We deflate this using Chemicals industry price deflators from the 1998 OECD *ISDB* database. The implied R&D stock for each importing country is constructed by multiplying R&D in constant US dollars of each source country by the value share of exports of that source country over the total of medical exports by all major pharmaceutical exporters we have R&D data for. These include eight of the ten source countries, with the exception

[5]We use the price deflator of the Chemicals industry for pharmaceuticals and the Manufacturing sector price deflator for other types of medical imports.

[6]R&D spending on other medical products is only available at an aggregate level that includes a broad set of non-medical categories such us 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.

of Belgium and Switzerland for which we have no R&D data. That is,

$$PHARD = \sum_{c=1}^{8} \frac{PHAEX_c}{\sum_{c=1}^{8} PHAEX_c} \times CRD_c,$$

where $PHAEX_c$ is pharmaceuticals exports in current \$US by source country c, and CRD_c is pharmaceuticals R&D expenditures in constant \$US by that source country.[7]

Third, we use a number of health output and health input data from the World Development Indicators (WDI) 2002 database. These include life expectancy at birth, infant mortality per thousand live births, male mortality per thousand male adults, and physicians per thousand people. We also obtained total population, and GDP per capita in PPP dollars from the same database. In addition to this we use calorie intake data from the Food and Agriculture Organization (FAO) database. We also obtained data on Latitude for each of the countries in our sample. We were able to put together all the above series for 83 countries, including the ten frontier source countries, for the period 1961 to 1995. The great majority of these series, including life expectancy, infant mortality, male mortality, calorie intake, and physicians are not available annually.

The scatter plots of the relationship between medical imports and health are in Figure 2. The first panel shows a positive correlation between medical imports and life expectancy (the correlation coefficient is 0.71). The correlation between imports and health is robust to the choice of health indicator: the other two panels show scatter plots between medical imports and male mortality/infant mortality rates (the correlation coefficients are -0.73 and -0.79, respectively). In the next section we examine systematically the health-medical imports relationship.

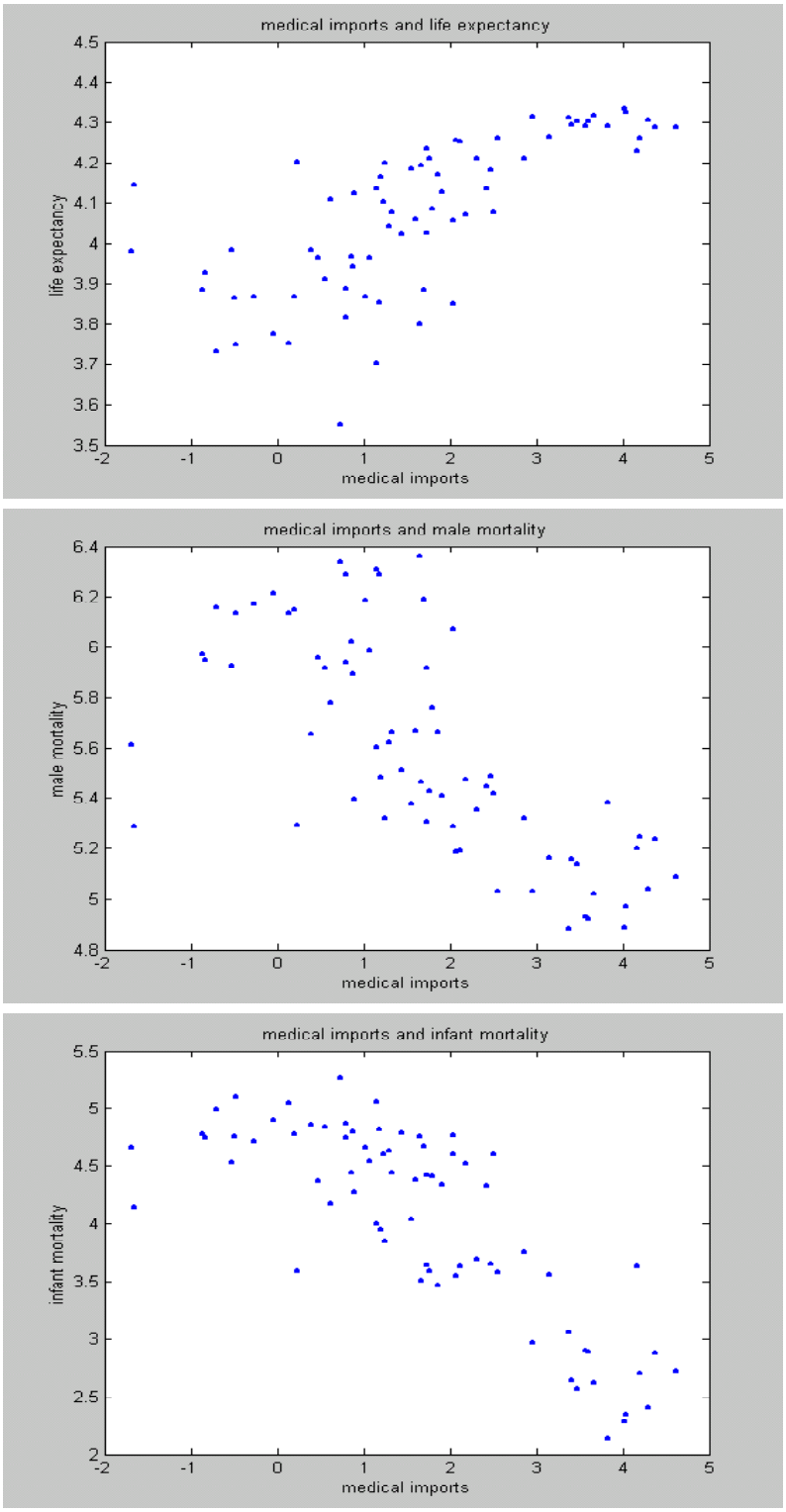
4 Empirical Results

4.1 Preliminary Evidence

Our main goal is to explore the relation between medical imports embodying foreign R&D-induced technology and health status. We begin with the cross-sectional relationship between medical imports and health during our sample period (1961-1995). We measure health status by three indicators: average life expectancy at birth (*LIFE*), infant mortality (*INFANT*) and male mortality

[7]This R&D measure which is similar to the one used in the technology diffusion literature, has little cross-sectional variation by construction. It only varies across different importing countries to the degree that one country imports more from a more R&D intensive source country (say from the US) rather than a less R&D intensive country (say Italy.)

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.

(*MALE*) rates per 1000 persons. In Table 1 we report unconditional correlations for a cross-section of 73 countries.[8] All variables are in natural logs.

Health status has a strong relation with per capita pharmaceutical imports (*PHAIM*) in Table 1: the correlation between *PHAIM* and the three health indicators is 0.65, -0.74 and -0.68, respectively. We also consider a more general measure of medical-related imports (*MEDIM*) that includes, in addition to pharmaceuticals, imports of medical equipment and other broadly defined medical imports. The respective correlations with life expectancy, infant mortality, and male mortality are now stronger: 0.71, -0.79, and -0.73. Finally, we consider a measure of imports of medical capital and equipment (*MCAPIM*) by summing SITC categories 774 (electric apparatus for medical purposes) and 872 (medical instruments and appliances). The correlation between *MCAPIM* and life expectancy, infant mortality, and male mortality rates are even higher: 0.83, -0.88 , and -0.83.

One might argue that, to a large extent, the high correlations between 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 affects health outcomes. Table 4.1 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 (percentage of females aged 15 to 24 that are illiterate or *ILLIT*); this is strongly correlated with life expectancy (-0.82). Moreover, proximity to the tropics (*TROP*) has a negative correlation with life expectancy (-0.49). In the empirical model we 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. To investigate this we relate pharmaceutical and other medical imports (*MEDIM*, *MCAPIM* and *PHAIM*) to health advancements in importing countries. A complementary hypothesis is that health technologies developed in advanced economies diffuse to the rest of the world in the form of ideas, not necessarily embodied in physical imports. One

[8]We exclude 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 pharamceutical exporting nations) in order to focus on health status in countries that depend on imports of foreign medical technology.

can think of medical methods and practices that, once developed in advanced economies, filter to the rest of the world. In order to evaluate this, for each importing country we construct a measure of medical R&D stock as the import-weighted sum of foreign (source-country) R&D expenditures (*PHARD*).[9] The implicit assumption is that a non-R&D performing country's stock of health knowledge or technology is implied by the health technology stock 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 technology stock. Table 1 shows that *PHARD* is also correlated with health outcomes but less so than the physical imports measures: the correlation between *PHARD* and life expectancy is 0.31.

4.2 Baseline Cross-Section Estimation Results

In this section we present our baseline cross-sectional results. In subsequent sections, we examine the robustness of these results to subsamples that are obtained by using the Hansen (2000) endogenous splitting methodology. In addition to splitting our whole sample, we also examine the robustness of our baseline results to considering panel estimation and therefore adding the time dimension to our analysis.

The correlations in Table 2 provide only suggestive evidence regarding the relationship between pharmaceutical and other medical imports and health status. In this section we control for a variety of determinants of health status in order to test systematically the link between imports of health technology (embodied either in medical imports or flowing across borders via ideas) and health status. For example, as mentioned previously, the positive correlation between medical imports and health outcomes could be due to the positive effect of per capita income on both variables. Consequently, in the regression model we control for initial income per capita and also include a number of health inputs through which income affects health outcomes. In order to control for per capita income, we include the exogenous component of income per person as a determinant of health status. This is because of the endogeneity between income and health status. We obtain the exogenous component of income as that part of income 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

[9]The exact definition of *PHARD* was given in the previous section

Table 2: Unconditional cross-sectional correlations across 68 countries

	MEDIM	MCAPIM	PHAIM	PHARD	TROP	CAL	PHYSI	ILLIT	WATER	LIFE	I
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	
MALE	-0.73	-0.83	-0.68	-0.22	0.56	-0.81	-0.89	0.73	-0.73	-0.94	
INC	0.81	0.86	0.77	0.17	-0.53	0.77	0.80	-0.59	0.69	0.77	

Notes: All variables are in natural logarithms. Complete data is available for 68 countries. MEDIM is aggregate medical imports in co defined in the data section of the paper , MCAPIM is imports of medical machinery and equimpment in constant $US per person, P imports in constant $US per person (category 54 of the OECD ITCS data described as Medicinal and pharmaceutical products,) PH specific pharmaceutical -industry 3522- R&D in millions of constant dollars implied by R&D of source country multiplied by import sha in total medical imports from 8 source counries for which R&D data are available, TROP is tropical proximity defined as the inverse latitude, CAL is total calories per person, PHYSI is number of physicians per thousand people, ILLIT is Illiteracy rate as a percenta 24, WATER is percentage of population with access to Improved water source, LIFE is life expectancy, INFANT is infant mortality, and INC is GDP per capita in constant $US in 1961.

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 health status, or equivalently, it is exogenous to health. *GADP* enters positively and significantly as a determinant of per capita income (with an estimated coefficient of 2.88 and t-statistic = 8.12) and explains 46 percent of the overall variation.

Our main measure of health is life expectancy; this is the measure used by most studies on health in developing economies.[10] Initially, our main indicator of medical technology imports is *MEDIM*. All variables are considered in natural logs so our estimates can be interpreted as health elasticities. We report elasticities from the baseline specification in the first panel of Table 3. In addition to the baseline specification, we look at two alternative measures of medical imports: medical capital and equipment (*MCAPIM*) in the second panel of Table 3 and pharmaceutical imports alone (*PHAIM*) in the third panel of Table 3. In Tables 4 and 5 we consider two alternative measures of health outcomes, male mortality and infant mortality, respectively.

The estimates reported in the first panel of Table 3 support the existence of an embodied medical technology link via imports of medical products in the first place. Also we find evidence for a disembodied flow of medical technology via the direct flow of ideas in the second instance. The estimate of *MEDIM* is positive and significant in all specifications[11] and so is that of *PHARD* in models 2 and 5. The elasticity of life expectancy with respect to medical imports ranges from a high of 0.056 to a low of 0.012 across the various specifications in the table. We conclude that 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 0.4 to 1.4 percent. The elasticity of medical imports is consistently about one third that of per capita income. Our results indicate 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 policy even in the short term.

The elasticity of life expectancy with respect to pharmaceutical R&D ranges from a high of 0.16

[10]It should be noted that the correlation between the three indicators of health status is large. 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.

[11]The exception is Model (5) where the estimate of medical imports is marginally insignificant (p-value = 0.134).

Table 3: 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[3]	.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 = 0.11, [3]p-value = 0.165. Heteroskedasticity-consistent standard errors are used in constructing t-statistics.

for models (2) and (3) to a (statistically insignificant) low of 0.03 in model (7). We note that this elasticity is robust across models (2)-(4) but is more than halved once we account for the number of physicians in model (5). Greater availability of physicians is one of the main means through which the ideas channel operates and 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) to (7).

As mentioned, per capita income has a positive impact on health outcomes in Table 3. Nevertheless, once we control for calories intake and physicians in model (5), the magnitude of income's impact on life expectancy falls by half; this suggests that income affects life expectancy largely via its impact on food consumption and medical care. When we also account for female illiteracy, then the estimated coefficient for the impact of income is reduced to 0.037, 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: as we saw in Table 2 and in models (1)-(3) in panel A of Table 3, initial per capita income levels are indeed highly correlated with life expectancy. We suggest that this strong relation can be explained in large part once we account for the level of health inputs, such us calorie intake, physicians, and education, through which income affects life expectancy.

Proximity to the tropics (*TROP*) is introduced in model (3) to control for the exogenous rate of disease arrival: it has a negative effect on life expectancy and an estimated elasticity of -0.02. In models (4) and (5) we introduce two other health inputs: food consumption and medical care availability. We measure these by calorie intake (*CAL*) and the number of physicians per thousand people (*PHYSI*). As expected, both have a strong positive impact on life expectancy. The elasticity of calorie intake is the largest among all explanatory variables (0.473 in model 4); the estimate of calorie intake decreases and becomes insignificant once we account for physicians, illiteracy, and access to improved waters source in models (5) to (7). 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 safe water access in model (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 most oft-cited propositions in the development literature is the link between female literacy and health. We find strong evidence to support this proposition. We note that when we include *ILLIT* the sample is reduced by eleven observations. We note that the estimated elasticity of life expectancy with respect to imports is higher (and is now statistically

Table 4: 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 standard errors are used in constructing t-statistics.

significant) compared to the estimated coefficient in Model (5). 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).[12] This suggests that the higher estimates for the impact of imports on health status in model (6) are not due to sample specificity, but rather due to the inclusion of a previously omitted but important determinant of health status. Model (6) explains about 86 percent of the cross-sectional variation in life expectancy when accounting for medical technology spillovers in the form of medical imports and pharmaceutical R&D, geography and climate in the form of tropical proximity, income per capita, and health inputs such as calorie intake and physician availability, and the fraction of young females without a basic level of education.

Adding access to an improved water source (*WATER*) in model (7) does not improve the fit of our regression nor does it have a big effect on our estimated coefficients for the impact of medical technology on life expectancy. Moreover, *WATER* is not estimated to be a significant determinant of health when we control for a variety of other health inputs. However, when we include *WATER* in a specification with only medical imports and income on the right-hand-side, then the estimated coefficient for *WATER* (not reported in the Tables) is 0.189 and strongly significant beyond the one percent level of significance. In fact, when we do not include total calories, physicians, illiteracy rates, and distance to tropics, *WATER* always enters as a strong and significant determinant of health outcomes (life expectancy, infant mortality, or male mortality rates) along with medical imports and income. This suggests that *WATER* is highly collinear with other health inputs[13] such us calorie intake and physicians so that it loses its significance when these are included in the specification.

The results are similar when, in the second panel of Table 3, we consider imports of medical capital and equipment (*MCAMIM*) rather than aggregate medical imports. It is interesting to note that *MCAPIM* has an even stronger positive (and statistically significant) impact on life expectancy than *MEDIM*, with elasticity estimates ranging from a high of 0.081 to a low of 0.017. Moreover, the direct impact of pharmaceutical R&D on life expectancy remains positive and significant,

[12]Specifically, the correlations of *MEDIM*, *MEDCAPIM*, and *PHAIM* with 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, respectively, 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.

[13]Indeed, the correlation of WATER with CAL and PHYSICIANS is 73 and 78 percent respectively.

Table 5: Cross-country infant mortality regressions

Specif. 1	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
MEDIM	−.2176* (−5.69)	−.2134* (−5.99)	−.2135* (−5.82)	−.1665* (−3.51)	−.1331* (−3.52)	−.0846** (−2.43)	−.0826** (−2.28)
INC	−.8511* (−9.32)	−.8705* (−9.17)	−.8708* (−9.36)	−.7814* (−5.85)	−.7502* (−6.39)	−.1838*** (−1.68)	−.1765 (−1.57)
PHARD	—	−.3092* (−3.17)	−.3092* (−3.15)	−.3109* (−3.22)	−.1119 (−0.97)	.0145 (0.12)	.0170 (0.14)
TROP	—	—	−.0006 (−0.01)	−.0236 (−0.52)	−.0659 (−1.31)	−.0476 (−1.45)	−.0482 (−1.48)
CAL	—	—	—	−.9012 (−1.51)	−.1567 (−.25)	−.0048 (−0.01)	.0009 (0.001)
PHYSI	—	—	—	—	−.1759* (−2.78)	−.0851 (−1.30)	−.0814 (−1.24)
ILLIT	—	—	—	—	—	.2645* (6.05)	.2653* (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* (−7.99)	−.2535* (−7.36)	−.2579* (−6.98)	−.2214* (−3.82)	−.1779* (−3.48)	−.1008** (−2.38)	−.1009* (−2.11)
INC	−.6487* (−7.25)	−.6893* (−7.48)	−.6943* (−7.58)	−.6615* (−5.34)	−.6569* (−5.89)	−.1527 (−1.49)	−.1528 (−1.47)
PHARD	—	−.1589*** (−1.73)	−.1562*** (−1.68)	−.1783*** (−1.82)	−.0324 (−0.27)	.0660 (0.55)	.0659 (0.55)
TROP	—	—	−.0182 (−0.46)	−.0327 (−0.74)	−.0652 (−1.34)	−.0508 (−1.55)	−.0508 (−1.57)
CAL	—	—	—	−.5883 (−0.94)	−.0489 (−0.07)	.0899 (0.18)	.0898 (0.17)
PHYSI	—	—	—	—	−.1478** (−2.41)	−.0827 (−1.28)	−.0827 (−1.27)
ILLIT	—	—	—	—	—	.2597* (5.83)	.2597* (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* (−4.49)	−.1879* (−5.04)	−.1872* (−4.89)	−.1417* (−3.09)	−.1139* (−3.30)	−.0704** (−2.19)	−.0689** (−2.06)
INC	−.9404* (−9.89)	−.9361* (−9.68)	−.9330* (−9.91)	−.8137* (−6.07)	−.7672* (−6.61)	−.2049*** (−1.92)	−.2000*** (−1.86)
PHARD	—	−.3509* (−3.70)	−.3508* (−3.69)	−.3402* (−3.63)	−.1231 (−1.06)	.0039 (0.03)	.0057 (0.05)
TROP	—	—	.0054 (0.12)	−.0178 (−0.39)	−.0616 (−1.24)	−.0478 (−1.47)	−.0483 (−1.49)
CAL	—	—	—	−0.9895*** (−1.67)	−.2015 (−0.32)	−.0104 (−0.02)	−.0052 (−0.01)
PHYSI	—	—	—	—	−.1814* (−2.88)	−.0934 (−1.44)	−.0907 (−1.39)
ILLIT	—	—	—	—	—	.2648* (6.15)	.2652* (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 standard errors are used in constructing t-statistics.

but is now smaller than the specification with *MEDIM*, ranging from a high of 0.126 to a low (and statistically insignificant) estimate of 0.028. If imports of medical capital and equipment embody 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 then reduce the potential of spuriously attributing embodied R&D spillovers to direct flows of ideas as measured by the R&D stock variable (*PHARD*).

Finally, the results are similar but somewhat weaker for the embodied technological spillovers hypothesis when, in the third panel of Table 3, we utilize pharmaceutical imports alone (*PHAIM*). Elasticities of life expectancy with respect to pharmaceutical imports range from a high of 0.046 to a low of 0.01 (marginally statistically insignificant p-value $= 0.165$). At the same time, pharmaceutical R&D now plays a more important role with elasticities ranging from a high of 0.175 to a (statistically insignificant) low of 0.039.

We explore the relation between foreign medical technology and health outcomes further in Tables 4 and 5, where instead of life expectancy we measure health by male mortality rates and infant mortality rates, respectively. Compared to the estimates for life expectancy, the results for male mortality rates and infant mortality rates present both similarities and some interesting differences.

Model (2) of Table 4 shows that the elasticity of male mortality with respect to medical imports is about twice that of the life expectancy elasticity. The estimate of this elasticity becomes (marginally) insignificant once we control for the number of physicians or female illiteracy. The estimated elasticity of male mortality rates with respect to pharmaceutical R&D is also about twice as high as that for life expectancy. Once again, the estimated impact diminishes and is no longer statistically significant once we account for physicians or the illiteracy rate. As mentioned previously, the number of physicians also captures in part the flow of ideas and thus acts to reduce the estimated impact of our other measure of this channel. Proximity to the tropics increases male mortality rates in model 3, but this effect is no longer significant when we allow for the number of physicians or for female illiteracy. Calorie intake per person has a strong negative impact on male mortality rates with an elasticity of -1.192 in model (4); it is more than twice as large as for life expectancy.[14] The elasticity of male mortality rates with respect to physicians, is relatively high: -0.17 in model (5) and -0.15 in model (6.) The (absolute) values of these elasticities are more than

[14]Once more, it is not significant once we control for physicians or illiteracy.

two times greater than the elasticity of life expectancy. Illiteracy of young women has no statistically significant effect on male mortality. We conjecture 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 5, we report estimates for the impact of medical technology and other health inputs on infant mortality rates. In model (2) the (absolute) value of the elasticity of infant mortality rates with respect to medical imports is about four times the life expectancy elasticity and about two times the male mortality elasticity. Infant mortality (absolute) elasticities range from a maximum of -0.218 to a minimum -0.085. The estimated elasticity of infant mortality rates with respect to pharmaceutical R&D is -0.31 in models (2) to (4), but becomes insignificant once we introduce the number of physicians in model (5). Proximity to the tropics does not seem to have any impact on infant mortality rates, and neither does Calories per person. The elasticity of infant mortality rates with respect to physicians is -0.17. As argued before, illiteracy among young women has a (strong) significant effect on infant mortality rates: in model (6), a 10 percent increase in female illiteracy is associated with a 2.7 percent increase in infant mortality. Increases in per capita income have the greatest impact on infant mortality: the estimated elasticity of infant mortality with respect to per capita income is several times higher than that for life expectancy or male mortality. We also note that whereas per capita income is significant in all models, about 75 percent of its impact goes away as soon as we control for female illiteracy rates, suggesting that the latter largely accounts for the impact of income on infant mortality rates.

4.3 Robustness Analysis

We start our sensitivity analyses of the results by considering first the robustness of our results to different subsamples of countries. Subsequently, we expand our cross-sectional estimation to panel estimation taking advantage of the time dimension in the data.

4.3.1 Endogenous Subsample Splitting

Unlike numerous other studies that *trivially* split the data into subsamples, here we follow Hansen (2000) to search for endogenously determined subsamples in the data. Hansen (2000) develops a statistical theory of threshold estimation in the linear regression context that allows for cross-

section observations. Least squares estimation is considered, and an asymptotic distribution theory for the regression estimates is developed. The main advantage of Hansen's methodology over the regression-tree model (i.e. 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.[15]

We choose Model 5 of the cross-sectional analysis as our baseline regression equation. The reason for selecting Model 5 out of the seven models considered above is twofold: First, it allows for a large number of observations *and* regressors. Second, it is generally the model with the least pronounced effect of medical imports – our key explanatory variable – on health as measured by life expectancy (see Table 1). In particular, we search for endogenously determined subsamples in the data by using our three proxies for imported medical technology (*MEDIM*, *MCAPIM*, *PHAIM*) as potential threshold variables. The entire exercise involves nine variations of Model 5 (three panels, in each of Tables 3-5) using as threshold variable the one used as a regressor in the particular regression considered (for example if we consider Model 5 in the top panel of Table 3, we also use *MEDIM* as our potential threshold variable). To save space and since the results are qualitatively similar for the three dependent variables proxing for health (life expectancy, male mortality and infant mortality), in what follows we present results using only life expectancy as the depended variables (as in the three panels of Table 3).[16] 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. We have also applied this threshold methodology using Model 6 and results are reported in Figure A1 and Table A2.

Since Hansen's statistical theory allows for one threshold for each threshold variable, we proceed using the heteroskedasticity-consistent Lagrange Multiplier test for a threshold developed by Hansen (1996). First, we consider Model 5 with *MEDIM* as the regressor and potential threshold variable. It is shown that the threshold model using *MEDIM* is significant with p-value of 0.06, indicating that there exists a sample split based on medical imports. The top panel in Figure 3 presents the normalized likelihood ratio sequence $LR_n^*(\gamma)$ statistic as a function of the output threshold. The least-squares estimate γ is the value that minimizes the function $LR_n^*(\gamma)$ which occurs at $\hat{\gamma} = 1.79$. The asymptotic 95% critical value (7.35) is shown by the dotted line and where it crosses $LR_n^*(\gamma)$

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

[16] The rest of the results using Model 5 are available from the authors upon request.

Figure 3: Likelihood ratio statistics as a function of threshold variables

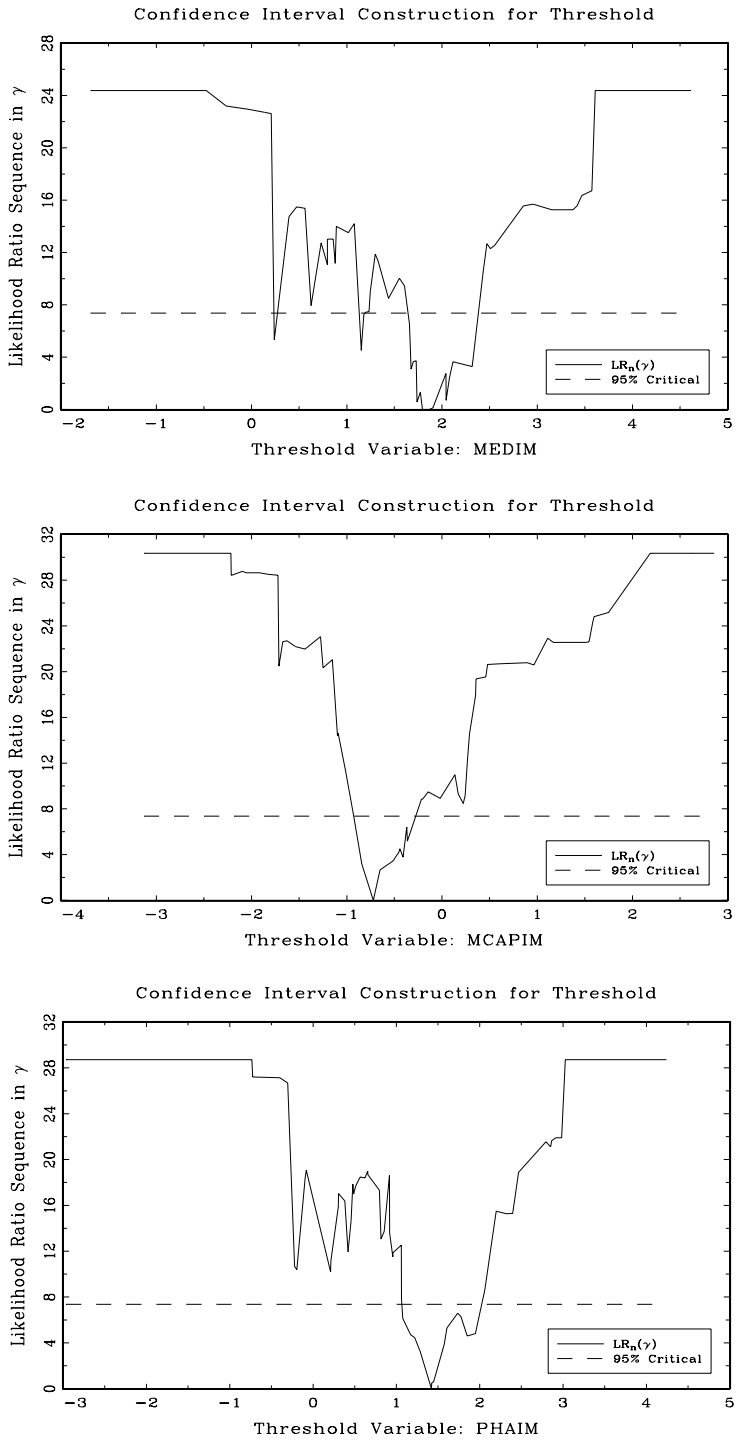
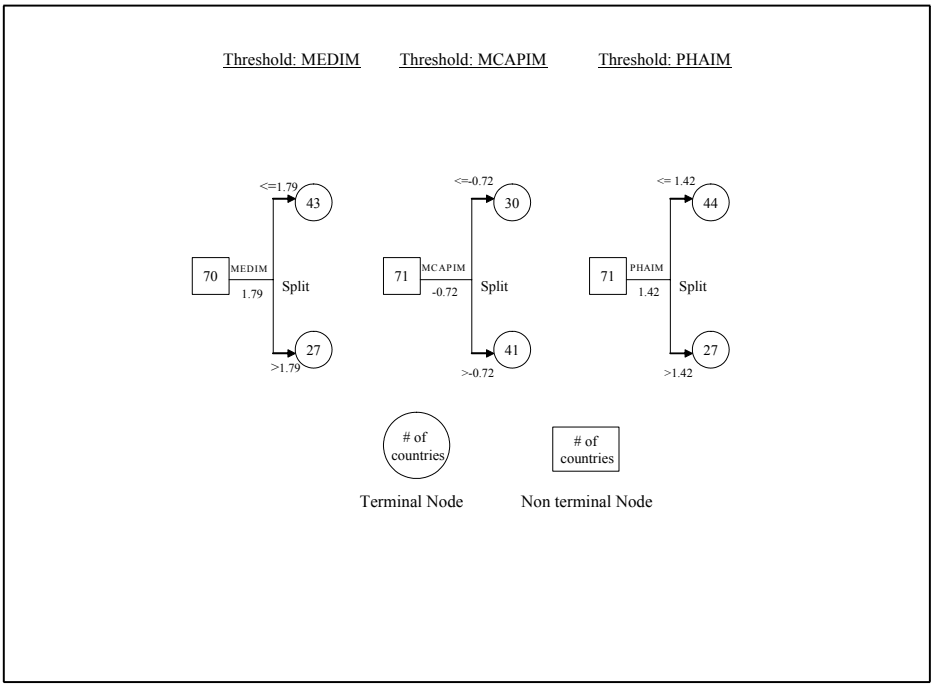


Table 6: Regression trees obtained using thresohold estimation



displays the confidence set $[0.24, 2.31]$. The *MEDIM* threshold variable divides our full sample of 70 countries into a low-literacy group (below 1.79) with 43 countries and a high-literacy group (above 1.79.) with 27 countries.

Second, we consider *MCAPIM* as a threshold variable. We find that the threshold model using *MCAPIM* is highly significant with p-value of 0.002, pointing to strong evidence of a split based on medical capital imports. The middle panel in Figure 3 panel B presents the normalized likelihood ratio statistic as a function of the *MCAPIM*. The point estimate for the literacy threshold is $\hat{\gamma} = -0.72$ with the 95% confidence interval $[-0.84, -0.36]$. The *MCAPIM* variable splits the entire sample of 71 countries into two subsamples; the low importing sample (below -0.72) with 30 countries, and the high importing sample (above -0.72) with 41 countries.

Finally, *PHAIM* is considered as a threshold variable. The bootstrap test statistic for this variable is also significant with p-value of 0.039. In particular, $\hat{\gamma} = 1.42$ with the 95% confidence interval $[1.08, 1.95]$ and the entire sample of 71 countries can be split into two subsamples with 44 countries (above 1.42) and 27 countries (below 1.42). The bottom panel in Figure 3 presents the normalized likelihood ratio statistic as a function of the *PHAIM*.

Table 7: 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		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 8: Subsample regressions

Specif.	**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 standarderrors are used in constructing t-statistics.

Figure 3 presents regression tree diagrams that illustrate our threshold estimation results obtained under the three regressions using *MEDIM*, *MCAPIM*, *PHAIM* respectively. Non-terminal nodes are illustrated by squares whereas terminal nodes are illustrated by circles. The numbers inside the squares and circles show the number of countries in each node. The point estimates for each threshold variable are presented on the rays connecting the nodes. Table 6 presents the countries in the three pairs of subsamples, respective to the three models. These results suggest that regardless of medical import proxy there is evidence of a split in the data.

4.3.2 Subsample regression results

Next, we turn attention to estimation of the regression coefficients of the three variations of Model 5 for the two identified regimes. Table 8 presents these coefficient estimates.

Notice that estimates for virtually all regressors considered vary extensively in magnitude and significance in each pair of subsamples for each of the three variations of Model 5. More importantly, the subsample estimates reveal that the effect of medical imports on life expectancy (see estimates in row 3 of Table 8) 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. In the model using MEDIM as a threshold variable (see rows 2-3 of Table 4), it is

shown that the coefficient estimates for MEDIM is -0.002 and insignificant in Subsample 1, and 0.019 and significant at the 10% level in Subsample 2. Similarly, in the model using MCAPIM as a threshold variable (rows 4-5 of Table 8), it is shown that the coefficient estimates for MCAPIM is -0.009 and insignificant in Subsample 1, and 0.046 and significant at the 1% level in Subsample 2. Finally, in the model using PHAIM as a threshold (rows 6-7 of Table 8) it is shown that the relevant variable coefficient estimates are -0.007 and insignificant in Subsample 1, whereas 0.012 but significant only at the 17% level.

In summary, these results reveal a new important insight in the relationship between medical imports and health; namely that only countries over a threshold of medical imports can reap of the benefits of existing medical technologies in terms of improved health. Subsequently, this result is of particular interest to policy makers concerned with this issue and it is worth their careful consideration

4.3.3 Panel Estimation

[This model needs more work in explaining the results] In addition to checking the robustness of our baseline results to alternative subsamples, we try to explore the time dimension of our data using panel estimation. In particular, we divide our sample period 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 1. 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), compared to the respective correlations of 0.71, -0.79, and -0.73 in the cross-section. The same goes for the correlations between our three measures of health status and each of our other two measures of imports. A notable exception relates to the correlations between health status and pharmaceutical R&D: they are much higher than for the cross section.[17] We report the unconditional panel correlations below and undertake a more careful examination of the relationship between health status with our measures of technological diffusion and other health inputs next.

Table 9 report estimates of the relationship between medical technology diffusion (and other health inputs) and health status measured by life expectancy, male mortality rates, and infant

[17]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 9: 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*	.0221*	.0123**	.0703*	.0336*	.0148**	.0411*	.0188**	.0127*
	(6.67)	(2.57)	(2.39)	(10.22)	(3.92)	(2.12)	(5.66)	(2.23)	(2.70)
INC	.1308*	.0886*	.0255**	.0784*	.0704*	.0225***	.1444*	.0908*	.0252**
	(8.05)	(5.17)	(2.07)	(5.10)	(3.84)	(1.87)	(9.01)	(5.43)	(2.07)
PHARD	—	.1535*	.0607*	—	.1351*	.0527*	—	.1584*	.0645*
		(10.11)	(3.52)		(9.16)	(3.14)		(10.20)	(3.74)
CAL	—	.4180*	.1313*	—	.3584*	.1199**	—	.4287*	.1318*
		(7.34)	(2.60)		(6.29)	(2.33)		(7.58)	(2.64)
PHYSI	—	—	.0441*	—	—	.0435*	—	—	.0437*
			(4.88)			(4.64)			(4.89)
ILLIT	—	—	−.0316*	—	—	−.0308*	—	—	−.0316*
			(−4.79)			(−4.57)			(−4.85)
WATER	—	—	.0139	—	—	.0127	—	—	.0131
			(.99)			(0.89)			(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*	−.0549**	−.0227	−.1692*	−.0829*	−.0314[1]	−.1119*	−.0469**	−.0234
	(−7.47)	(−2.31)	(−1.06)	(−10.73)	(−3.39)	(−1.27)	(−6.34)	(−2.04)	(−1.19)
INC	−.2696*	−.2003**	−.0881**	−.1576*	−.1556*	−.0809***	−.3004*	−.2042*	−.0822**
	(−6.95)	(−4.66)	(−2.06)	(−4.30)	(−3.34)	(−1.92)	(−7.81)	(−4.96)	(−1.97)
PHARD	—	−.2962*	−.0465	—	−.2497*	−.0309	—	−.3078**	−.0529
		(−7.39)	(−0.69)		(−6.17)	(−0.49)		(−7.65)	(−0.78)
CAL	—	−1.016*	−.2837	—	−.8668*	−.2555	—	−1.047*	−.2802
		(−6.47)	(−1.55)		(−5.45)	(−1.37)		(−6.63)	(−1.54)
PHYSI	—	—	−.1612*	—	—	−.1588*	—	—	−.1610*
			(−5.90)			(−5.78)			(−5.95)
ILLIT	—	—	.0336	—	—	.0315	—	—	.0343
			(1.53)			(1.40)			(1.57)
WATER	—	—	−.0439	—	—	−.0397	—	—	.0529
			(−1.06)			(−0.97)			(−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*	−.2139*	−.1238*	−.3301*	−.2745*	−.1369*	−.2405*	−.1859*	−.1131*
	(−9.83)	(−5.75)	(−5.29)	(−14.05)	(−7.23)	(−4.43)	(−8.49)	(−4.93)	(−5.33)
INC	−.6639*	−.5971*	−.0893	−.4794*	−.4736*	−.0613	−.7258*	−.6272*	−.0993***
	(−10.75)	(−6.89)	(−1.57)	(−8.20)	(−5.52)	(−1.12)	(−11.73)	(−7.24)	(−1.77)
PHARD	—	−.3371*	−.0719	—	−.1876*	.0081	—	−.3806*	−.0937
		(−5.03)	(−0.96)		(−2.82)	(0.11)		(−5.51)	(−1.25)
CAL	—	−1.064*	−.2784	—	−.7387**	−.1876	—	−1.156*	−.3084
		(−3.39)	(−1.09)		(−2.26)	(−0.71)		(−3.71)	(−1.23)
PHYSI	—	—	−.0372	—	—	−.0355	—	—	−.0385
			(−1.05)			(−0.96)			(−1.10)
ILLIT	—	—	.2918*	—	—	.2863*	—	—	.2929*
			(11.68)			(11.45)			(11.79)
WATER	—	—	.0132	—	—	.0193	—	—	.0078
			(0.27)			(0.39)			(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, [1]p-value = 0.208. Heteroskedasticity-consistent standard errors are use

mortality rates respectively. The table includes three panels: one for each of three measures of health output. We consider all health inputs utilized in our cross-sectional analysis, with the exception of tropical proximity since that measure is inherently cross-sectional.[18] In all models, we control for income per capita using the exogenous component of income as discussed in the previous section. We also control for the presence of global exogenous shocks specific to each decade by introducing time-specific dummy variables. AA look at the baseline model in the first column of Table 9 reveals that the estimated coefficients are very close to those for the cross section.

The results in Models 1, 4 and 7 of Table 6 support the embodied medical technology diffusion hypothesis with the estimated coefficients usually quite close to those in the cross section. Model 7 is less supportive of the embodied medical technology diffusion hypothesis when we consider male mortality rates, with coefficients being positive but insignificant at conventional levels of significance. On the other hand, pharmaceutical R&D enters positively for Model 4 providing additional support for the disembodied technological diffusion hypothesis. Additional health inputs such as calorie intake, physician availability, and female illiteracy are always significant determinants of life expectancy as is income per capita. The estimates in Table 9 for the impact of medical technology and other health inputs on male mortality rates tell a similar story as for life expectancy. Finally, the estimates for the impact of medical technology on infant mortality rates in Table 9 are much more supportive of the embodied technology diffusion hypothesis with the estimated coefficients for the impact of medical imports statistically significant for all four models and all three panels.

5 Conclusion

While a great deal has been written about the beneficial effects of international R&D spillovers from capital goods for both developed and developing economies, there has been no research to uncover any benefits from spillovers of medical technology. Our main hypothesis is that medical technologies resulting from R&D in advanced economies operating close to the medical frontier benefit, not only the countries originating these technologies, but also other nations, in terms of enhanced health status and productivity. 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

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

the rest of the world. The extent of these benefits depends on the amount of medical goods imported by each recipient nation, in the first instance, and by the size of medical R&D expenditures in the source countries a recipient country trades more intensively with, in the second instance.

In this paper we present a simple endogenous 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 rely on imports of foreign medical technology. In our main regression model 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 the form of ideas and that this diffusion is related to the intensity of trade between the recipient and each of the nations that perform medical R&D. As demands for more resources directed at controlling communicable diseases in developing economies are being voiced, our evidence points to the beneficial effect that efforts directed at increasing medical imports will have on health outcomes in developing economies.

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Appendix

Table A1: Mean Values of Data from the 73 Country Sample

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

Notes: The sources for these data are World Development Indicators (WDI, 2002), and OECD International Trade by Commodity (ITCS) databases. Summary statistics for the rest of the data used in this paper are available from the authors upon request.

Table A1: Mean Values of Data from the 73 Country Sample cont.

Country	**Code**	**Life Exp.**	**Male Mort.**	**Infant Mort.**	**Med. Imp.**	**Med. Cap. Imp.**	**Pharm. Imp.**
Korea, Rep.	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: The sources for these data are World Development Indicators (WDI, 2002), and OECD International Trade by Commodity (ITCS) databases. Summary statistics for the rest of the data used in this paper are available from the authors upon request.

Figure A1: Regression trees obtained using thresohold estimation (using Model 6)

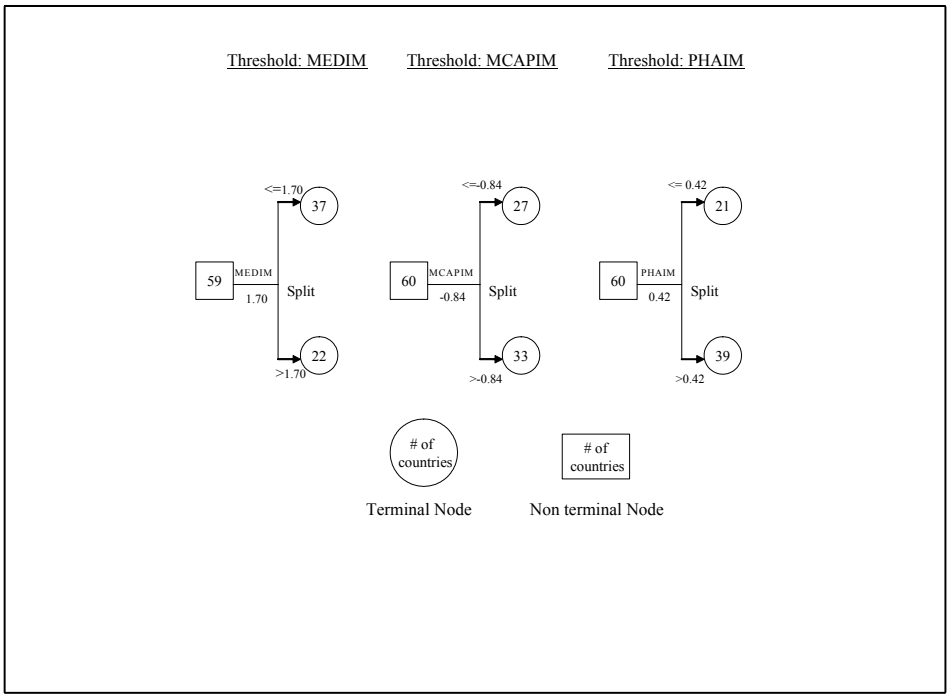

Table A2: Subsample regressions (using Model 6)

Specif. 1,2,3	**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 standarderrors are used in constructing t-statistics.

Table A3: Unconditional panel correlations across 68 countries

	MEDIM	MCAPIM	PHAIM	PHARD	TROP	CAL	PHYSI	ILLIT	WATER	LIFE	I
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	
MALE	-0.69	-0.80	-0.63	-0.45	0.53	-0.77	-0.88	0.73	-0.69	-0.92	
INC	0.59	0.66	0.56	0.05	-0.44	0.71	0.64	-0.59	0.69	0.66	

Notes: All variables are in natural logarithms. Complete data is available for 68 countries. and four sub-periods 1961-1969, 1970-1979,
For the definition of variables see Table 1 in the main text.