Human Development Research Paper 2010/32

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Research Paper

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Abstract

Three apparently contradictory stylized facts characterize the relationship between per capita incomes and life expectancy: (i) the existence of a strong correlation between the level of life expectancy and the level of per capita income, (ii) the absence of a significant correlation between changes in per capita income and changes in life expectancy, and (iii) the persistence of twin peaks in the distribution of life expectancy, despite their progressive disappearance from the income data. This paper seeks to reconcile these apparently contradictory findings. We argue that a data generating process in which there is a relationship between income and life expectancy for high levels of development but not for low ones can explain these stylized facts, while models that apply a uniform relationship to all countries cannot. We also argue that the slope of the relationship between income and life expectancy is significantly overestimated by standard cross-sectional estimates, with the true slope being much lower for some countries and not statistically significantly different from zero for others. Lastly, we provide evidence from an error-correction model showing that the elasticity of life expectancy to incomes has been declining both for countries at high and low levels of development. We suggest that these results can be interpreted as showing that income matters only for countries that are close enough to the world health technological frontier.

Keywords: Life expectancy, income growth, Preston curve, health determinants, Monte Carlo experiments.

JEL classification: I1, O15, N30, C15.

1 Introduction

This paper seeks to improve our understanding of the relationship between per capita income and health outcomes – in particular life expectancy - at the national level. Understanding this relationship requires us to make sense of the patterns present in the cross-country data. Regrettably, these appear to be contradictory. On the one hand, we see a strong positive association between per capita income and life expectancy in a cross-section of countries, suggesting a positive association between the two variables. On the other hand, we see the absence of a relationship in differences even over relatively long time spans, suggesting the absence of a relationship. Third, we see the persistence of twin peaks in the world distribution of life expectancy – even after high HIV countries are taken out of the sample – suggesting that different data generating processes may apply to different types of countries.

This paper argues that models in which the same empirical relationship is hypothesized to apply to both poor and rich countries cannot make sense of the evidence. In particular, we find that both a model that presumes the existence of a relationship between life expectancy and income across all countries and one that presumes the absence of that relationship for all countries are deficient in explaining the data. In contrast, we argue that a model in which the data generating process applying to countries at low levels of development is different from that applying at high levels of development can make sense of all of these apparently contradictory facts. We also show that standard cross-sectional estimates of the elasticity of life expectancy of income are systematically biased upward because they ignore this dual data generating process. We suggest that these results can be interpreted as showing that income matters only for countries that are close enough to the world health technological frontier.

The extent to which development policies aimed at improving people's health conditions are centered on per capita income is, at least partially, based on empirical evidence concerning the nature of the relationship between life expectancy and per capita income. As public resources are even scarcer in developing than in developed countries, it is imperative for policy makers to efficiently allocate the available resources across public health and income growth promoting policies.

The academic literature to date has not yet reached a consensus on the extent to which policies aimed at improving people's health conditions should be centered on economic growth. On the one hand, inspired by the impressive explanatory power of the cross-sectional relationship of per capita income and health condition indicators such as life expectancy first described by Preston (1975), it has been argued that per capita income should be given considerable weight in development policies. For example, Pritchett and Summers (1996), referring to empirical evidence that per capita income growth significantly reduces infant mortality, state that "raising per capita incomes will be an important component of any country's health strategy" (Pritchett and Summers, 1996, p. 844).[1] Filmer and

[1] To do justice to Pritchett and Summers (1996), we should mention that they acknowledge that, eventually, income growth may operate through "increased public and private spending on goods that directly or indirectly improve health" (Pritchett and Summers, 1996, p. 844), and that "investments specific to child health improvements are expected to be more cost effective in producing health gains than economic growth" (Pritchett and Summers, 1996, p. 865).

Prichett (1999) find that public health policies have only extremely small effects on health conditions; Filmer and Prichett (1999) also find that per capita income together with a dummy for a predominantly Muslim population, female education, income inequality and ethno-linguistic fractionalization are able to explain almost all the variation in infant mortality across countries[2], stating that "[w]hile there are poor countries with exceptionally good health status, properly accounting for income and other economic determinants leaves little to be explained by independent variations in health policy" (Filmer and Prichett, 1999, p. 1310). Pritchett and Viarengo (2010), reaffirm this point, and express concerns regarding a developing country government's ability to successfully implement health policies, even in those cases where policies at least in principle have a large potential to improve people's health conditions.

On the other hand, numerous authors question whether economic growth should be assigned a prominent role in development policies aimed at improving people's health conditions. Cutler et al. (2006) argue that public health policies (via the provision of sewage systems, removal of waste, clean water, information dissemination and health education) and increasingly the (international) diffusion of health knowledge have been more important for the rise of life expectancies across developed countries since the end of the 19th century. Easterlin (1999) also makes the case for the supremacy of public policy interventions over per capita income

[2]Their estimations, however, additionally include region dummies, several other dummies to indicate missing observations on explanatory variables, the percentage of the population living in urban areas, the fraction of the land in tropical zones, and the fraction of the population with access to safe water (the latter three turn out to be individually statistically insignificant). It is not obvious to what extent the impressive explanatory power stems from the inclusion of these variables.

for the improvement of health conditions during the last one and a half centuries. Preston (1975) argues that 75 to 90% of the growth in life expectancy is unrelated to a country's growth in per capita income. Given the accumulated knowledge and the broad range of effective health technologies available in the developed countries, large gains in life expectancy in developing countries should be viable by comparably inexpensive measures: vaccinations, safer sex, breastfeeding, vector control, (maternal) health education, rehydration and antibiotical therapies, alterations in contaminating behavior and internalized attitudes towards the sick, see Cutler et al. (2006). Diffusion and local adoption, which - in an era of globalization - should be feasible at rather low cost are key to this argument, see Deaton (2004).

In this paper, we provide empirical evidence in favor of the hypothesis that by endorsing development policies which facilitate the adoption of existing health technologies and knowledge, developing countries can expect to improve their people's health conditions to a much larger extent than by pursuing income growth-centered policies. To do so, we investigate the relationship between life expectancy and per capita income for two different country groups over the time period from 1970 to 2010. We find that the estimated income elasticity in the standard Preston curve is sizeably overstated due to the failure to control for countries' distance to the health technology frontier, and that catching up to the health technology frontier is much more important for expanding life expectancies in developing countries. To further back this result, we contrast the ability of different data generating processes (DGPs) for life expectancy to replicate the patterns we observe in the actual data. In particular, we initially focus on two polar DGPs: One in which per capita income is the sole determinant of life expectancy (the stable Preston curve), and another one in which the evolution of life expectancy is entirely independent of per capita income (the breakdown of the Preston curve). As none of these polar DGPs is able to replicate the patterns observed in the actual data, we investigate a third DGP representing our hypothesis that per capita income is of no importance for the determination of life expectancy in countries far away from the health technology frontier, but may be of some (even though very small) importance for countries close to the health technology frontier. We find that this mixing DGP is able to replicate the patterns we observe in the data. Furthermore, we investigate the evolution of the income elasticity over time within the standard Preston curve and within an error-correction model with time-varying coefficients. We find that the income elasticity of life expectancy has decreased over time even in countries close to the health technology frontier, and that there are indications that it has recently become statistically insignificant.

The remainder of this paper is structured as follows: Section 2 provides a brief summary of the evolution of life expectancy from the 18th century to the present day, some empirical evidence on the relationship between life expectancy and per capita income, and our core hypothesis that income effects of life expectancy are overstated due to the failure of controlling for countries' distance to the health technology frontier. In Section 3.1, we set up a simulation exercise that contrasts the ability of different DGPs, each representing a competing theory about the role of income in determining life expectancy, to replicate the patterns present in the actual data. In Section 4, we allow for long lags in the relationship between life expectancy and per capita income, and briefly investigate the evolution of the Preston curve over the last four decades. Finally, Section 4.2 concludes.

2 The Confounding Relationship Between Life Expectancy, per Capita Income and Technology

Health conditions all over the world have undergone substantial improvements during the last two centuries. Progress, however, has been everything but uniform across countries. The Western world happened to be at the vanguard, experiencing the conquest of infectious diseases in the 19th and beginning of the 20th century, and subsequently from the 1960s on the cardiovascular revolution. Developing countries have begun to trace the paths of developed countries in improving health conditions only recently. Many of the developing countries have displayed impressive track records since then, benefitting from already existing health technologies in the developed world, see Arriaga and Davis (1969) and Soares (2007). The heterogeneity in the progress of health conditions across countries and the nature of the progress itself are key to our argument in this paper. We therefore briefly outline the paths health conditions have taken over the last two centuries, before we present our key arguments.

In 1840 England, life expectancy at birth was about 40 years, but has reached 77 years by now, see Cutler et al. (2006). In the 19th century, undernourishment and ignorance concerning the modes of transmission as well as the causal agents rendered individuals particularly susceptible for infectious diseases, see Cutler et al. (2006) and Easterlin (1999). As a result, people's health conditions were determined to a large extent by the prevalence of infectious diseases such as tuberculosis, malaria, cholera and typhus. It seems that at that time higher disposable incomes enabled individuals to better meet basic needs, such as purchasing more and better food, appropriate clothing and shelter.[3] Thus, a positive relationship between the level of per capita income and health conditions should be expected to have prevailed at the time. However, it appears that the elasticity of health conditions with respect to income must have been rather small. For example, neither did life expectancy of English aristocrats exceed that of the rest of the population, despite presumably better nutrition, nor was mortality lower in well-fed populations of the same period, such as in the United States (Livi-Bacci, 1991 and Harris, 2004). Without knowledge of the mechanisms behind the most important pre-mature death causes at the time, money could not effectively buy protection, let alone cure, and did most likely have only a limited positive impact on health conditions.

From the 1850s on, modes of transmission of major communicable diseases responsible for large proportions of mortality (either directly or indirectly) were discovered, and preventive action as well as improved sanitation enabled people to counter adverse health outcomes, especially in urban areas.[4] From the 1880s

[3]In fact, numerous authors claim that improved nutrition was the main determinant of the large health improvements achieved until the beginning of the 20th century, see Fogel (1997).

[4]See Soares (2007) for an extensive discussion of alternative explanations stressing different

onwards, in addition to the modes of transmission, the causal agents of many communicable diseases were identified (the germ theory of disease), and health outcomes could be further improved. As a result, the epidemiological transition raised life expectancies at unprecedented paces: The expansion of the health technology frontier shifted the relationship between health conditions and per capita income upwards.

However, the epidemiological transition at that time mostly passed by today's developing countries. While high prices might have played a role in preventing today's developing countries from adopting new health technologies back then, other factors appear to have been at least as relevant, and presumably are even more so today as the prices of effective health technologies have fallen considerably. For example, incentives of local policymakers to improve health conditions by introducing effective health technologies might have been undermined by the limited local accountability of colonial governments and their disinterest in the indigenous people, see Acemoglu et al. (2001). Even nowadays, the lack of accountability of governments and administrations may constitute serious obstacles to health technology adoption. For example, Lake and Baum (2001) and Kudamatsu (2006) show that transition to democracy significantly reduces infant mortality; more generally, Franco et al. (2004) find a positive correlation between democracy, political rights and civil liberties on the one hand, and life expectancy, infant and maternal mortality on the other hand. Low levels of education might

determinants of health improvements, and an analysis of the cross-sectional and inter-temporal evolution of death causes as well as age mortality profiles.

have also hindered the local adoption of technologies and knowledge (Nelson and Phelps, 1966, and Benhabib and Spiegel, 2005). For example, Hobcraft (1993) shows that the effect of maternal education on health outcomes *inter alia* operates through greater cleanliness and increased utilization of health services. De Walque (2007, 2009) finds that educated individuals are more responsive to HIV/AIDS information campaigns and more readily adopt protective behaviors. A deficient institutional environment with bad governance might have been and continue to be another factor underlying the failure of developing countries to adopt technologies from the developed world (Keefer and Knack, 1997). For example, Gauri and Khaleghian (2002) find that the quality of a country's institutions is strongly related to immunization rate coverage and vaccine adoption.

Paralleling the evolution of health conditions, per capita incomes started to grow strongly in much of the Western world from the middle of the 19th century, but not in today's developing countries, see Pritchett (1997) and Bourguignon and Morrisson (2002). The divergence of economic and health conditions across the developed and the developing world formed the basis of the strong and, as we will argue, misrepresented as well as misinterpreted correlation between life expectancy and per capita income in the Preston curve. Figure 1 displays the cross-sectional relationship between life expectancy and per capita income in $t = 1970$ and $t = 2010$ for 136 countries.[5] The solid lines in the upper panels depict fitted

[5] See Appendix A.1 for a list of the countries included. Our results are based on a data set compiled by the Human Development Report Office in the United Nations Development Program. In order to ensure that our results are not contaminated by the effects of the HIV/AIDS epidemic, we drop all countries with an HIV prevalence rate greater than 5% in 2007 according to the World Bank's World Development Indicators. The high HIV prevalence countries are: Botswana, Central

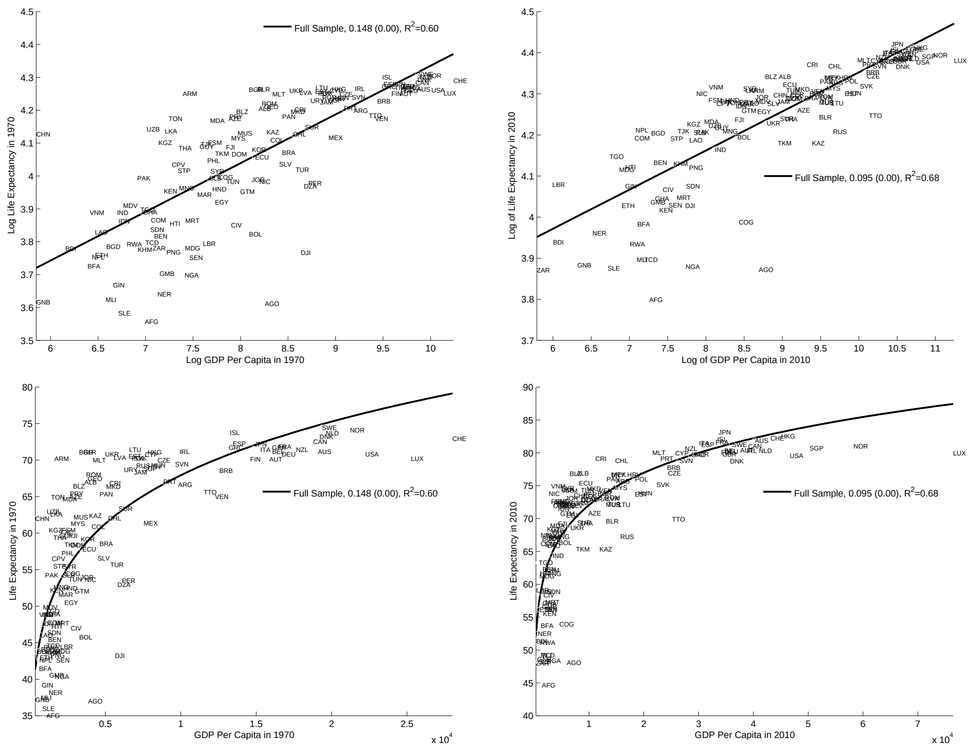
values from the regression

$$llife_{it} = a_t + b_t \cdot lgdp_{it} + u_{it}, \tag{1}$$

where $llife_{it}$ represents the logarithm of life expectancy, $lgdp_{it}$ the logarithm of per capita income, and $i = 1, 2, \ldots, N$ indexes countries. In the bottom panels, the Preston curve relationship is plotted in terms of the levels of life expectancy and per capita income based on the estimates from Equation (1). The legends provide the slope estimates, the associated p-values in parentheses and the R^2's.

African Republic, Guinea-Bissau, Lesotho, Malawi, Mozambique, Namibia, South Africa, Swaziland, Zambia and Zimbabwe. We also exclude major oil exporters as they are obvious outliers in the relationship between life expectancy and per capita income: Guinea-Bissau, Brunei, Bahrain, Kuwait, Libya, Quatar, Iran, Saudi Arabia, and the United Arab Emirates.

Figure 1: The Relationship Between per Capita Income and Life Expectancy



The main hypothesis in this paper is that the magnitude of the slope in the Preston curve is actually *spurious*, in the sense that it is highly overstated, as it does not only stem from life expectancy rising with increases in per capita income, but also from the fact that many developing countries considerably lag behind the health technology frontier, see Deaton (2007) for a similar point. Put differently, the Preston curve does not control for a country's distance to the health technology frontier, a case of omitted variables bias.

The hypothesis that the correlation between life expectancy and per capita income in the Preston curve mostly stems from the failure to account for countries' distance to the health technology frontier has three sets of implications. First, when splitting the countries into those closer to the health technology frontier and those farther away, two distinct Preston curves should be obtained, with the Preston curve of the countries closer to the health technology frontier located above that of countries farther away. Moreover, the Preston curve of countries farther away from the health technology frontier should be estimated quite imprecisely due to the large degree of cross-country heterogeneity regarding the distance to the health technology frontier, and should feature only a rather low explanatory power. We choose the Human Development Index (HDI) as a proxy for the distance to the frontier of health technology for several reasons. First, the HDI is constructed using literacy and enrollment rates and thus partly reflects a country's endowment with human capital that appears to be one precondition for the local adoption of health technologies. Second, the HDI includes per capita income, which is highly correlated with total factor productivity across countries, see Hall and Jones (1999), and which should be closely related to the extent of health technology adoption. Finally, although somewhat circular, it includes life expectancy, and thus directly proxies whether a country is likely to be in the group of countries close to or far away from the health technology frontier. Figure 2 revisits the Preston curves estimated in Equation (1) and displayed in Figure 1, but adds to the fitted values for the full sample those for low- and high-HDI countries.[6] The dash-dot line represents results for high-HDI countries and the dashed line for low-HDI

[6] The HDI threshold is 0.5. See Appendix A.1 for a listing of the low ($N_l = 37$) and high ($N_h = 99$) HDI countries.

countries. In each panel, the countries with the dark (black in the electronic version of this paper) labels are high-HDI countries, and the remaining ones are the low-HDI countries. Table 1 displays the coefficient estimates of Equation (1) for the full sample and the two sub-samples together with their p-values and the R^2's.

Figure 2: The Relationship Between per Capita Income and Life Expectancy for High- and Low-HDI Countries

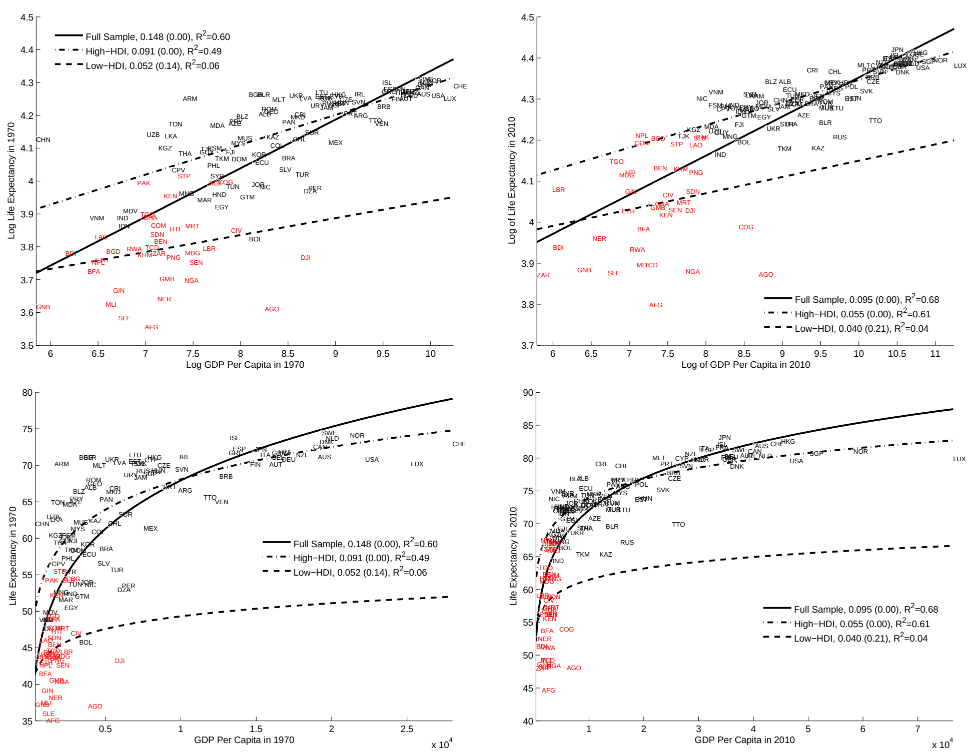


Table 1: Estimation Results for the Preston Curve

	$\widehat{b}_{1970}$	$\widehat{b}_{2010}$	$\widehat{a}_{1970}$	$\widehat{a}_{2010}$	R^2_{1970}	R^2_{2010}	N
Full Sample	0.148 (0.00)	0.095 (0.00)	2.854 (0.00)	3.400 (0.00)	0.60	0.68	136
Low-HDI Countries	0.052 (0.14)	0.040 (0.21)	3.424 (0.00)	3.753 (0.00)	0.06	0.04	37
High-HDI Countries	0.091 (0.00)	0.055 (0.00)	3.383 (0.00)	3.796 (0.00)	0.49	0.61	99

Note: The table displays the results from regressions of Equation (1), that is

$$llife_{it} = a_t + b_t \cdot lgdp_{it} + u_{it},$$

for $t = 1970, 2010$.

There are two distinct Preston curves for low- and high-HDI countries, and the Preston curve for the low-HDI countries is imprecisely estimated with almost nil explanatory power.[7] The slope of the full sample Preston curve is substantially higher than those of the low- and high-HDI countries. This confirms the first set of implications of our hypothesis. The difference in the intercepts could be interpreted as the distance to the health technology frontier. Inspecting differences in pre-mature mortality causes in low- and high-income countries in Table 4 supports this view: A substantial number of pre-mature deaths in low-income countries (respiratory infections such as pneumonia, perinatal deaths, diarrheal diseases, tuberculosis, malaria, DPT, measles and polio, and to some extent even HIV/AIDS) could be avoided by adopting existing health technologies and knowledge.

Second, a regression of changes in life expectancy on changes in per capita income should not produce positive and statistically significant slope estimates, especially

[7] The null of a single versus the alternative of two distinct Preston curves is rejected in formal Wald tests.

for the countries far away from the health technology frontier, as the improvements in life expectancy that can be achieved by the adoption of existing health technologies are much larger than the improvements that can be achieved by - if there are any - per capita income growth, and as countries' extent of adoption is generally heterogeneous. Moreover, for countries close to the health technology frontier, even if the heterogeneity in adoption should be expected to be much smaller, statistically insignificant results should be obtained if per capita income growth plays only a minor role for the determination of life expectancy relative to the expansion of the frontier. In first differences between 1970 and 2010, Equation (1) can be re-written as

$$\Delta llife_{i,2010} = \alpha + \beta \cdot \Delta lgdp_{i,2010} + e_{i,2010}, \quad (2)$$

where $\Delta x_{i,2010} = x_{i,2010} - x_{i,1970}$, $\alpha = \Delta a_{2010}, \beta = b_{2010}$, and $e_{i,2010} = \Delta b_{2010} \cdot lgdp_{i,1970} + \Delta u_{i,2010}$. The solid line in Figure 3 displays the relationship between the changes in the logarithms of life expectancy and per capita income as depicted in Equation (2) over the time period from 1970 to 2010 for the full sample and for high- as well as low-HDI countries separately, and Table 2 displays the corresponding coefficient estimates together with their p-values and the R^2's.

Figure 3: The Relationship Between the Changes in the Logarithms of per Capita Income and Life Expectancy

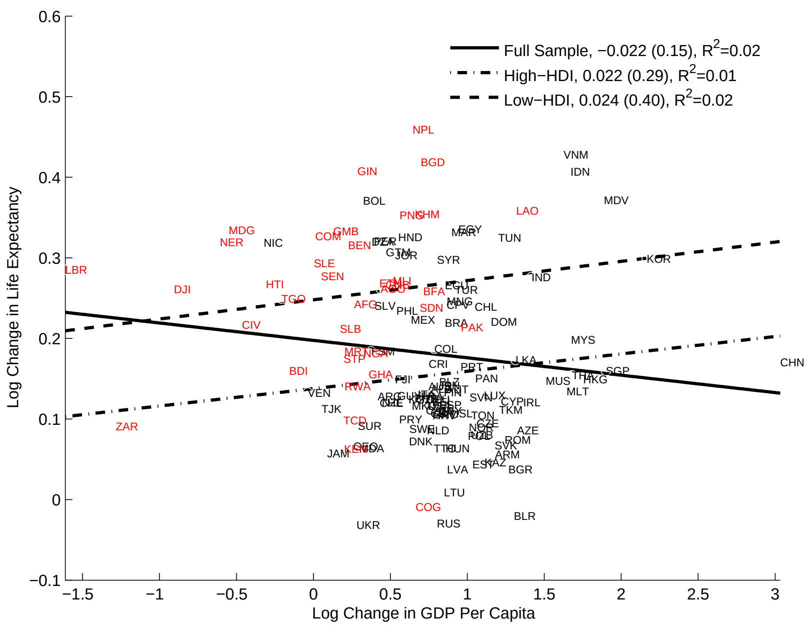


Table 2: Estimation Results for the Regression of the Changes in the Logarithms of Life Expectancy and per Capita Income

	$\widehat{\beta}$	$\widehat{\alpha}$	R^2	N
Full Sample	−0.022 (0.15)	0.198 (0.00)	0.02	136
Low-HDI Countries	0.024 (0.40)	0.248 (0.00)	0.02	37
High-HDI Countries	0.022 (0.29)	0.138 (0.00)	0.01	99

Note: The table displays the results from regressions of Equation (2), that is

$$\Delta llife_{i,2010} = \alpha + \beta \cdot \Delta lgdp_{i,2010} + e_{it}.$$

The correlation in changes is statistically insignificant for all samples, but closer to significance for the high-HDI than for the low-HDI sample, which confirms the second set of implications of our hypothesis. Similar result are found by Preston (1980), Easterly (1999), Deaton (2007) and Kenny (forthcoming).[8]

Yet a third implication of our hypothesis is that as developing countries manage to adopt technologies from the developed countries and move closer to the health technology frontier experiencing large gains in life expectancy, the Preston curve for the full sample should flatten. The results in Figure 1 for 1970 and 2010 confirm this implication. We provide more extensive evidence on this count in Section 4.

To provide more rigorous evidence for our hypothesis that the Preston curve is spuriously steep as it fails to control for the distance to the health technology frontier, in the next section we present the results to several simulation exercises.

3 The Relationship Between Life Expectancy and Income: Evidence from Simulations

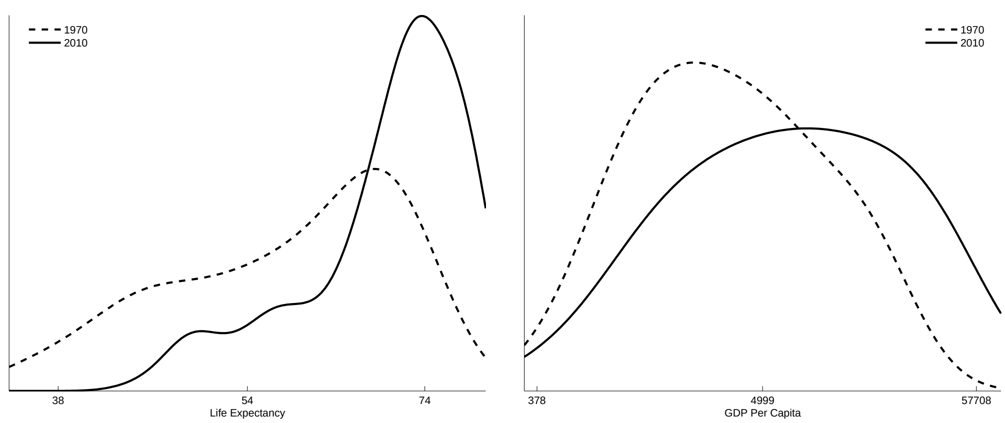
In this section we aim to assess the likelihood of different DGPs for life expectancy to generate the patterns observed in the actual data (the significant correlation in levels, the missing correlation in the changes regression, the R^2, etc.). To this end, we simulate life expectancy according to different DGPs and estimate key statis-

[8]Notice, however, that Pritchett and Summers (1996) do find a statistically significant, positive correlation for infant mortality. Also, Deaton (2004) obtains a statistically significant, positive correlation when weighting country observations by population; in this case, China features a large leverage on the correlation.

tics on the simulated data. Finally, we compare the distributions of the statistics estimated on the simulated data from each DGP to the statistics estimated on the actual data. We take the likelihood of the statistics estimated on the simulated data from a specific DGP concording with the statistics estimated on the actual data to represent the likelihood that the specific DGP is the true DGP of life expectancy.

A stylized fact that is going to be important in the following is that, as documented by Canning (2010), the cross-sectional distribution of life expectancy is characterized by twin peaks, whereas that for per capita income features only a single peak. The left-hand side panel of Figure 4 displays the cross-sectional distribution of life expectancy for both 1970 and 2010.

Figure 4: The Cross-Sectional Distribution of Life Expectancy and per Capita Income



There are two peaks in the cross-sectional distribution of life expectancy in 2010, one at about 52 and another at about 74 years. This twin-peak characterization of the cross-sectional distribution of life expectancy has, in fact, strengthened over time. The twin peaks are a manifestation of a specific group of countries continuously facing difficulties in adopting available health technologies, and thus being stuck in an equilibrium with lower life expectancy. In contrast to life expectancy, the twin peaks in the cross-sectional distribution of per capita income documented by Quah (1996) appear to be significantly weaker for 2010, see the right-hand side panel of Figure 4.[9]

3.1 The Simulation Setup

We distinguish between three competing DGPs:

1. a stable Preston curve ("Preston curve DGP"),
2. independent dynamics for all countries ("independent shocks DGP"),
3. independent dynamics for low-HDI countries and a Preston curve relationship for high-HDI countries ("Preston curve/independent shocks mixing DGP").

Essentially, while per capita income is the sole determinant of life expectancy in the Preston curve DGP, it is of no importance whatsoever in the independent shocks DGP. The Preston curve/independent shocks mixing DGP represents our hypothesis of two different sets of countries with a well identified Preston only for the countries close to the health technology frontier in a stylized form.

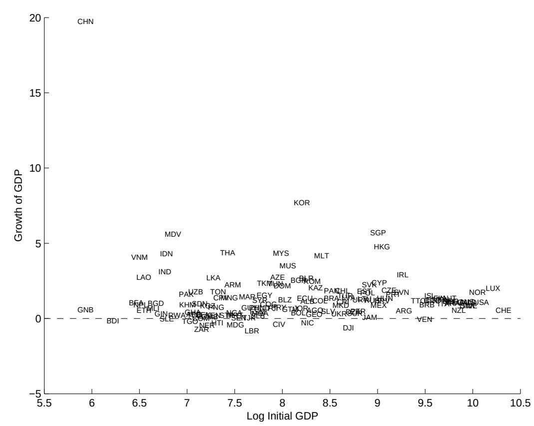
[9] The twin peaks in the cross-sectional distribution of life expectancy remain when controlling for the lower level of average life expectancy in Sub-Saharan African countries, see Figure 18 in the Appendix.

The same simulated per capita income series is used for all DGPs. We describe the DGP of per capita income in Section 3.1.1, the Preston curve DGP in Section 3.1.2, the independent shocks DGP in Section 3.1.3, and the Preston curve/independent shocks mixing DGP in Section 3.1.4.

3.1.1 The Data Generating Process for per Capita Income

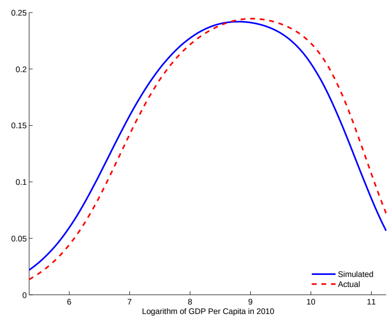
Figure 5 shows a scatter plot of the growth in per capita income against the log of per capita income in 1970.

Figure 5: Initial Log per Capita Income and Subsequent Income Growth



There does not appear to be unconditional β-convergence in per capita income. To simulate per capita income data and to replicate its actual cross-sectional distribution reasonably well, we partition the set of actual growth rates in quantiles, and obtain random growth rates by re-sampling for each quantile separately. Using the random growth rates and actual per capita income values in 1970, we obtain a simulated per capita income series $\left\{\widetilde{gdp}_{it}\right\}_{t=2010;i=1,2,...,N}$. Figure 6 compares the actual cross-sectional distribution of per capita income in 2010 with the average of the cross-sectional distributions of simulated per capita income across all replications of our experiment.

Figure 6: Cross-Sectional Distribution of per Capita Income in 2010



The cross-sectional distribution of simulated per capita income appears to be reasonably close to the actual cross-sectional distribution.

3.1.2 The Preston Curve Data Generating Process

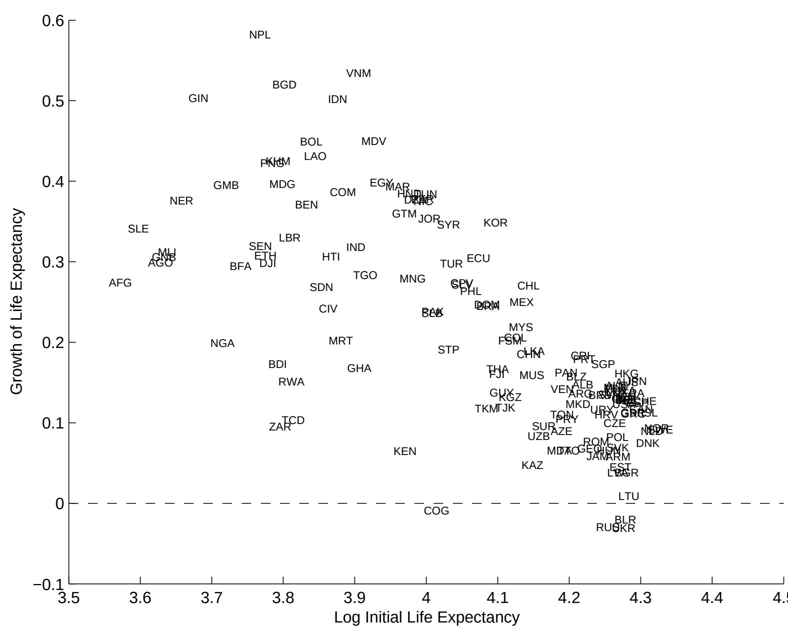
To obtain simulated life expectancy data based on the Preston curve DGP, we use the Preston curve estimates $\widehat{a}_t, \widehat{b}_t, \widehat{\sigma}_{u,t}$ for $t = 1970$ and $t = 2010$ shown in Figure 1 and Table 1. We generate a simulated life expectancy series $\left\{\widetilde{life}_{it}^{Preston}\right\}_{t=2010;i=1,2,...,N}$ using the simulated per capita income series $\left\{\widetilde{gdp}_{it}\right\}_{t=2010;i=1,2,...,N}$, the estimated parameters $\widehat{a}_{2010}, \widehat{b}_{2010}$ of the Preston curve and a random shock $\widetilde{u}_{i2010} = \rho \cdot \widehat{u}_{i1970} + v_{i2010},\ v \sim N(0, \sigma_v^2)$ in

$$\widetilde{llife}_{i,2010}^{Preston} = \widehat{a}_{2010} + \widehat{b}_{2010} \cdot \widetilde{lgdp}_{i,2010} + \widetilde{u}_{i,2010}. \tag{3}$$

3.1.3 The Independent Shocks Data Generating Process

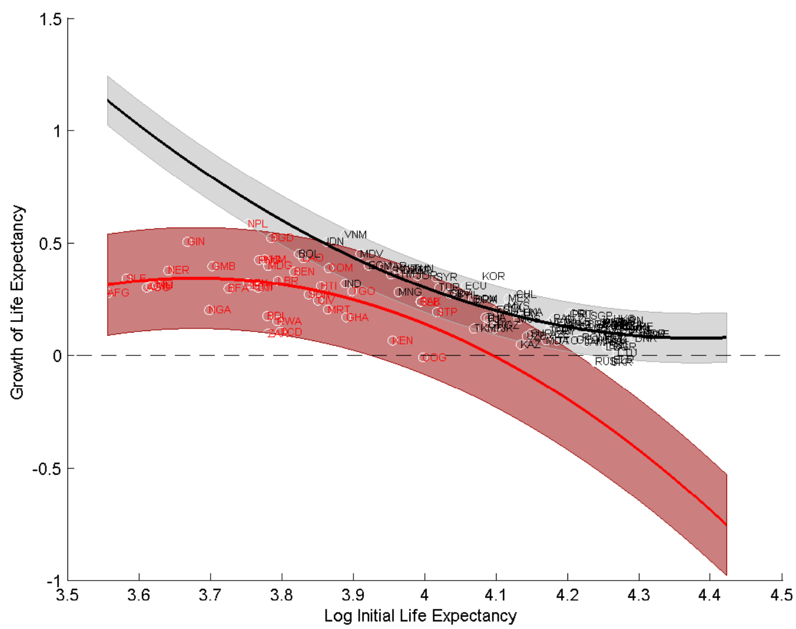
In contrast to the Preston curve DGP, under the independent shocks DGP the evolution of life expectancy is entirely independent from that of income. Figure 7 shows a scatter plot of the growth of life expectancy over the time period from 1970 to 2010 against the logarithm of life expectancy in 1970.

Figure 7: Initial Life Expectancy and Subsequent Life Expectancy Growth



There appear to be two regimes of life expectancy convergence countries can fall into, one in which countries converge to high levels of life expectancy and another one in which countries converge to low levels of life expectancy. Figure 8 shows fitted values from regressions of the growth in life expectancy over the time period from 1970 to 2010 on a second-order polynomial in the logarithm of life expectancy in 1970 together with confidence bands, estimated separately for high and low-HDI countries.[10]

Figure 8: Fitted Values for Initial Life Expectancy and Subsequent Life Expectancy Growth



We use the fitted values and the confidence bands of the convergence regressions to draw random growth rates of life expectancy for the low- and high-HDI countries. Using these growth rates together with life expectancy levels in 1970, we generate a simulated life expectancy series $\left\{\widetilde{life}_{it}^{IndepShocks}\right\}_{t=2010;i=1,2,...,N}$.

[10]The results are robust to using first-order polynomials.

3.1.4 The Preston Curve/Independent Shocks Mixing Data Generating Process

Under the Preston curve/independent shocks mixing DGP we split our sample into low- and high-HDI countries. For the high-HDI countries, we simulate life expectancy data for 2010 using the Preston curve DGP described in Section 3.1.2, but using the Preston curve parameter estimates based on the high-HDI sample only, see Figure 1 and the third row of Table 1. For the low-HDI countries, we generate simulated life expectancy data independently from per capita income according to the independent shocks DGP. Combining the Preston curve DGP simulated life expectancy data with the independent shocks life expectancy data yields a simulated life expectancy series $\left\{\widetilde{life}_{it}^{Preston/IndepShocks}\right\}_{t=2010;i=1,2,...,N}$.

3.2 Results

In each replication $r = 1, 2, \ldots, 5000$ of the Monte Carlo experiment, we estimate the following regressions

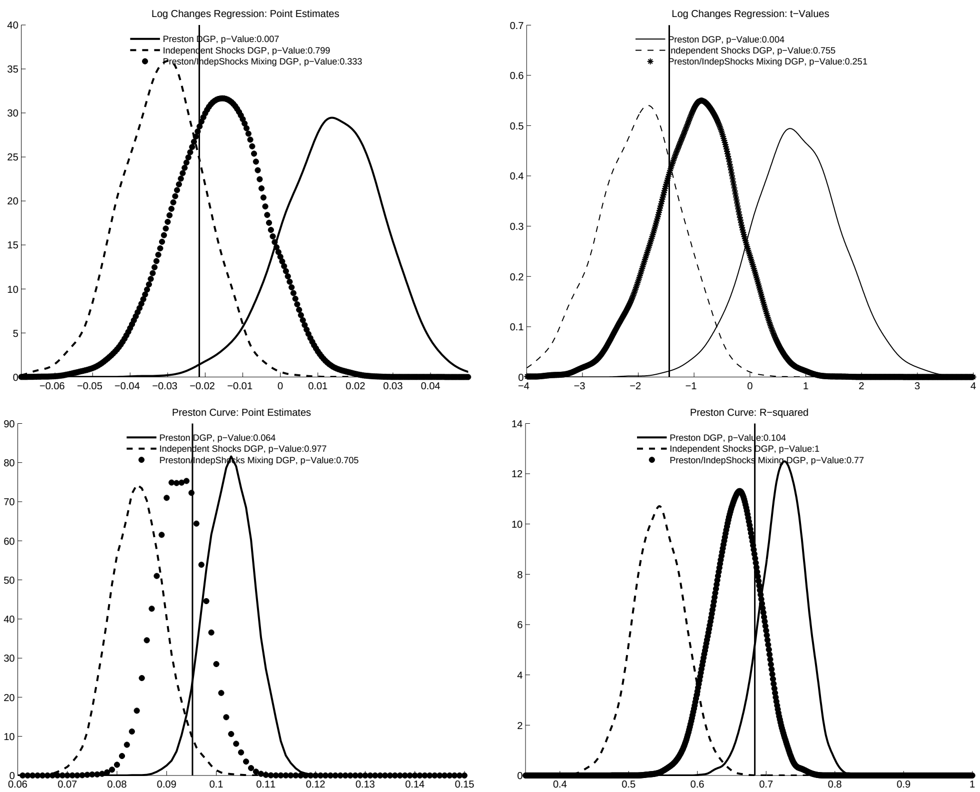
$$\begin{aligned}
\Delta\widetilde{llife}_i^{(j,r)} &= \delta^{(j,r)} + \gamma^{(j,r)} \cdot \Delta\widetilde{lgdp}_i^{(r)} + e_i^{(j,r)}, \\
\widetilde{llife}_i^{(j,r)} &= c^{(j,r)} + d^{(j,r)} \cdot \widetilde{lgdp}_i^{(r)} + w_i^{(j,r)},
\end{aligned}$$

using the simulated data

$$j \in \{\text{Preston, Independent Shocks, Preston/Independent Shocks Mixing}\}, \quad (4)$$

and store $\widehat{\gamma}^{(j,r)}$, $\widehat{d}^{(j,r)}$, the associated t-values and the R^2's. The distributions of the statistics estimated on the simulated data are displayed in Figure 9. The solid lines depict the distribution of the statistics estimated on the data from the Preston curve DGP, the dashed lines the distribution of the statistics estimated on the data from the independent shocks DGP, and the circled lines the distribution of the statistics estimated on the data from the Preston curve/independent shocks mixing DGP. The vertical lines represent the value of the corresponding statistic obtained from the actual data. The legends provide p-values for one-sided tests of the null hypothesis $H_0 : B_{median} > Z$, where B_{median} is the median of the simulated distribution of the statistic in question, and Z is the statistic estimated from the actual data.

Figure 9: Monte Carlo Results

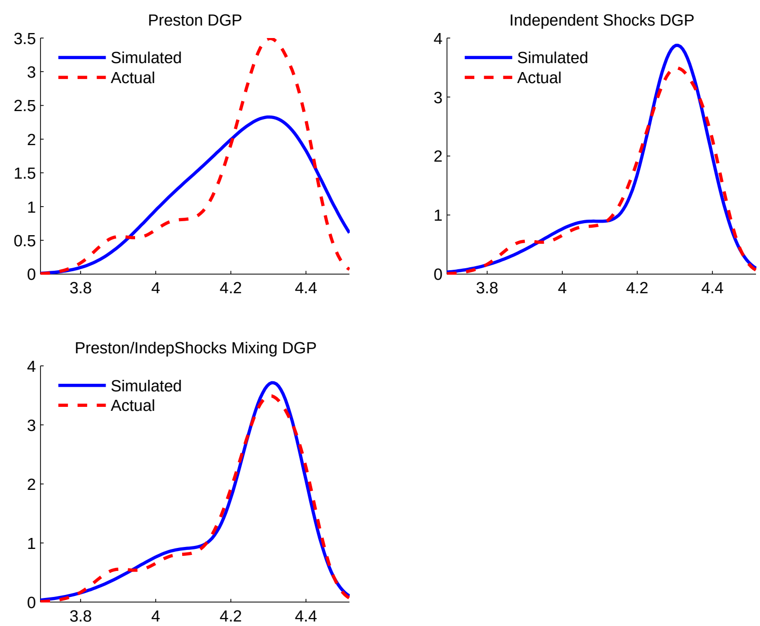


The first four columns in Table 5 provide the p-values and critical values (in brackets below) for two-sided tests of the hypothesis $H_0 : B_{median} = Z$ for the statistics displayed in Figure 9.

While the independent shocks DGP is likely to generate results for the regression of changes in the logarithm of life expectancy on changes in the logarithm of per capita income in Equation (2) that are similar to those obtained from the actual data, it fails to replicate the results for the Preston curve regression in Equation (1). The Preston curve DGP, in turn, is unlikely to replicate especially the results for the changes regression in Equation (2), and also less likely to replicate the results from the Preston curve regression in Equation (1) than the other DGPs. Finally, the Preston curve/independent shocks mixing DGP is likely to replicate *all* the results found in the actual data.

Figure 10 displays the averages of the simulated cross-sectional distributions of life expectancy for each of the DGPs we consider together with the actual cross-sectional distribution of life expectancy in 2010.

Figure 10: Cross-Sectional Distribution of Life Expectancy in 2010



Eyeballing suggests that the independent shocks DGP and the Preston curve/independent shocks mixing DGP are able to replicate the twin peaks in the cross-sectional distribution of life expectancy in 2010 reasonably well, but that the Preston curve

DGP fails to do so. The second to the last column in Table 5 reports *p*-values of Kolmogorov-Smirnov tests for the null hypothesis that the cross-sectional distribution of simulated life expectancy coincides with the actual cross-sectional distribution of life expectancy. While the null hypothesis that the actual cross-sectional distribution of life expectancy in 2010 is the same as that obtained from the independent shocks DGP and the Preston curve/independent shocks mixing DGPs cannot be rejected, the test rejects the equality of distributions for the Preston curve DGP.

To summarize the results, it appears rather unlikely that the patterns observed in the actual data are generated by an underlying DGP as represented either by a single, stable Preston curve relationship valid for all countries or completely independent shocks to life expectancy and per capita income. The simulations indicate that the patterns found in the actual data are much more likely to be generated by a mixture of the Preston curve and the independent shocks DGP.

3.3 Robustness: The Double Preston Curve DGP

In this Section, we look at a double Preston curve DGP that interpretes our hypothesis of two different sets of countries with a well identified Preston only for the countries close to the health technology frontier in the form of two distinct Preston curves. Notice that in terms of policy recommendations, the double Preston curve DGP and the Preston curve/independent shocks mixing DGP are very similar, as both imply that in order to improve life expectancy countries far away from the health technology frontier should aim to foster health technology adoption rather than spur income growth. For the double Preston curve DGP we use the estimates of the Preston curve parameters for the low- and the high-HDI countries in Table 1, and for the low- and the high-HDI countries construct simulated life expectancy data as in the Preston curve DGP in Section 3.1.2. The results are depicted in Figures 11 and 12, as well as in Table 6.

Figure 11: Monte Carlo Results for the Double Preston Curve DGP

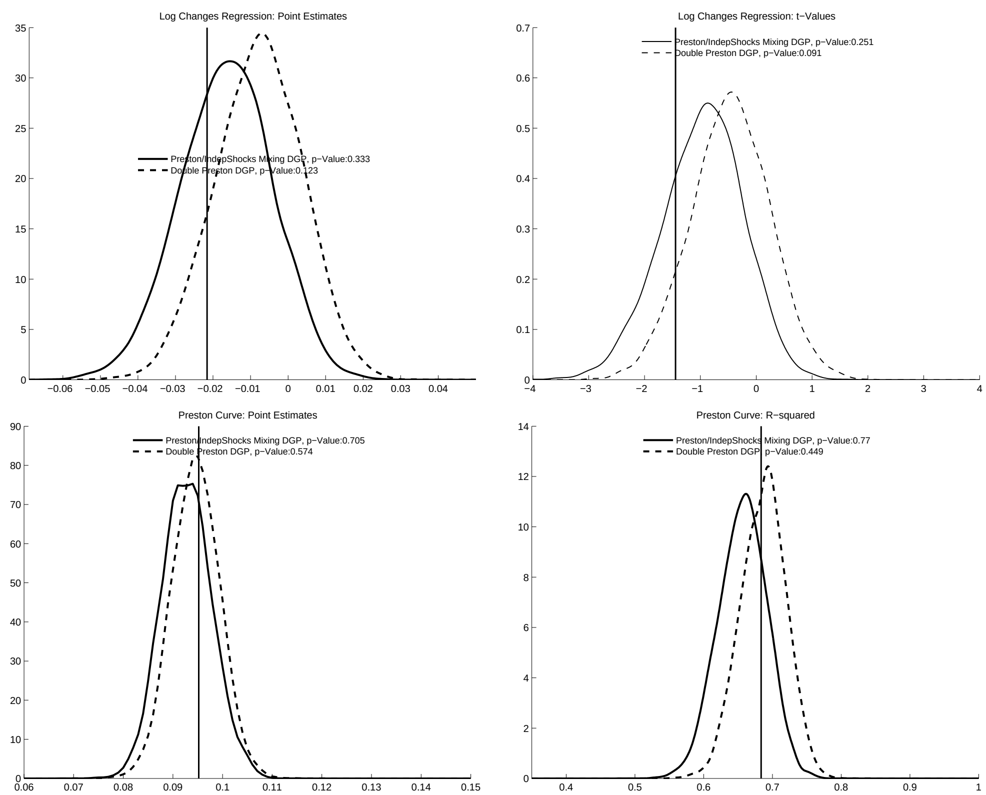
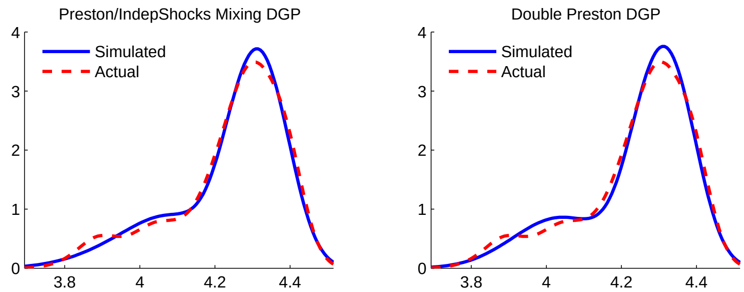


Figure 12: Cross-Sectional Distribution of Life Expectancy in 2010 for the Double Preston Curve DGP



The results for the double Preston curve DGP are very similar to those from the Preston curve/independent shocks mixing DGP. This is probably because the Preston curve is statistically insignificant for the low HD countries in the actual data.

4 The Breakdown of the Preston Curve

We have argued so far that the correlation of life expectancy and per capita income in the standard Preston curve is overstated because of the failure to control for developing relative to developed countries' systematically farther distance from the health technology frontier. In this section, we provide evidence that the elasticity of life expectancy with respect to per capita income for countries *close* to the frontier has declined over the last couple of decades, and might have even turned statistically insignificant more recently. To do so, we implement an empirical framework that (i) incorporates both long-run equilibrium dynamics as well as short-run transitional adjustments, and (ii) allows for inter-temporal coefficient variation: A time-varying coefficients error-correction model (ECM). To get a sense of what accounting for long lags does, we first explore the relationship between life expectancy and per capita income in a way analogous to Section 2 using a stylized ECM focusing only on (i). In a second step, we estimate a fully-fledged time-varying coefficients ECM to investigate how the relationship between the levels of life expectancy and per capita income has evolved over the last four decades.

4.1 The Relationship Between Life Expectancy and per Capita Income with Long Lags

Taking into account initial deviations from a long-run Preston curve and allowing for long lags in the relationship between life expectancy and per capita income might be key to explain the missing correlation in the changes regression of Equation (2), see Easterly (1999) and Pritchett and Viarengo (2010). For example, if a country given its per capita income level in 1970 had a level of life expectancy lower than that predicted by the Preston curve, and if the country's level of life expectancy converges to the predicted level of life expectancy only slowly over time, then we should observe the country's level of life expectancy to increase over time by a larger number of years than would be predicted by the change in per capita income. The noise stemming from neglecting initial conditions could be a reason for the lack of a significant correlation in Equation (2).

A stylized model linking life expectancy and per capita income with a long lag span, such as

$$llife_{i,2010} = \tau + \kappa \cdot llife_{i,1970} + \gamma_0 \cdot lgdp_{i,2010} + \gamma_1 \cdot lgdp_{i1970} + \nu_{i,2010}, \qquad (5)$$

can be used to address these issues. Re-written as an ECM, Equation (5) becomes

$$\begin{aligned} \Delta llife_{i,2010} &= \tau + (\kappa - 1) \cdot llife_{i,1970} + (\gamma_0 + \gamma_1) \cdot lgdp_{i,2010} + \gamma_0 \cdot \Delta lgdp_{i,2010} + \nu_{i,2010} \\ &= \varphi \cdot (llife_{i,1970} - a - b \cdot lgdp_{i,1970}) + \gamma_0 \cdot \Delta lgdp_{i,2010} + \nu_{i,2010}, \qquad (6) \end{aligned}$$

where $\varphi = \kappa - 1$, $a = -\tau/\varphi$, $b = -(\gamma_0 + \gamma_1)/\varphi$, and $\Delta x_{i.2010} = x_{i,2010} - x_{i,1970}$. In this error-correction framework, the transitional dynamics and the long-run equilibrium level relationship between life expectancy and per capita income are modelled simultaneously. As long as $\varphi < 0$, Equation (6) implies that changes in life expectancy do not only respond to current changes in per capita income, but also to deviations of a country's initial value of life expectancy from the value predicted by the long-run Preston curve.

The upper panel of Figure 13 displays for the full sample the fitted values for the long-run Preston curve upon estimation of Equation (6) and controlling for transitional dynamics. The bottom panels display the results for the low- and the high-HDI countries.[11] Figure 14 displays the relationship between the change in the logarithm of life expectancy and the change in the logarithm of per capita income

[11]The country samples are plotted in different panels because the scatter plots are *conditional* scatter plots and for each country sample the conditioning set is different.

controlling for initial deviations from a long-run Preston curve. Table 3 provides a summary of the results, also featuring the implied half lives of deviations from the long-run Preston curve.

Figure 13: The Relationship Between per Capita Income and Life Expectancy with Long Lags

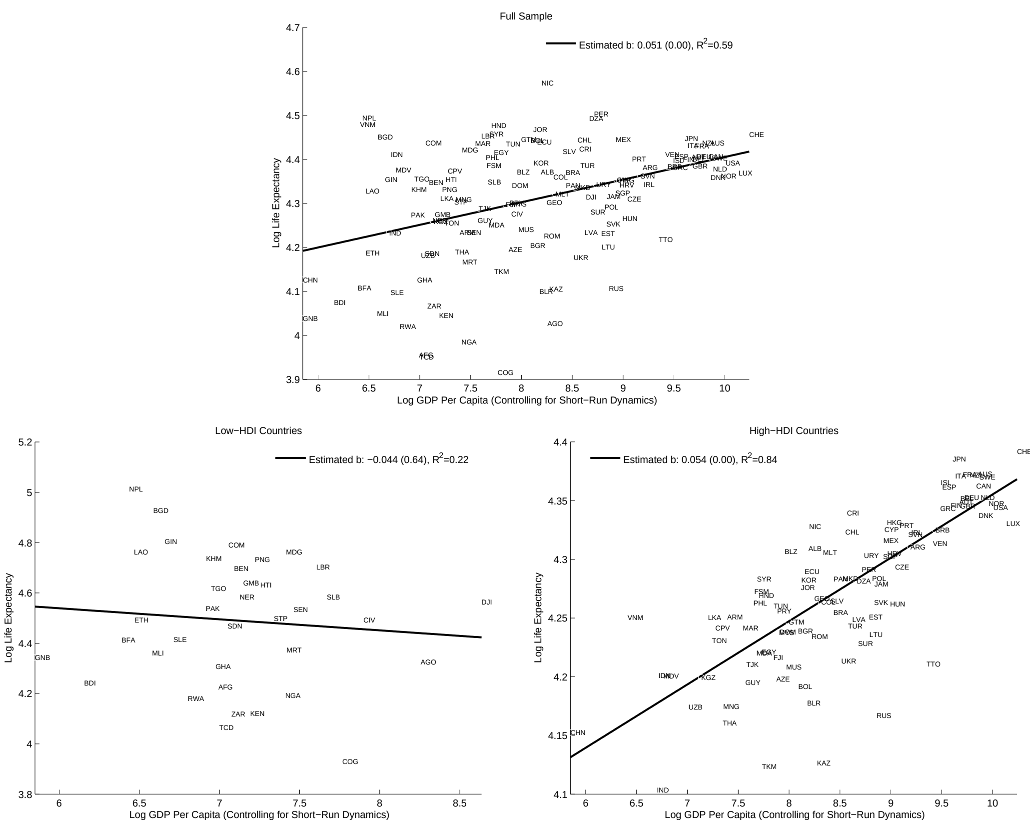


Figure 14: The Relationship Between the Changes in the Logarithms of per Capita Income and Life Expectancy with Long Lags

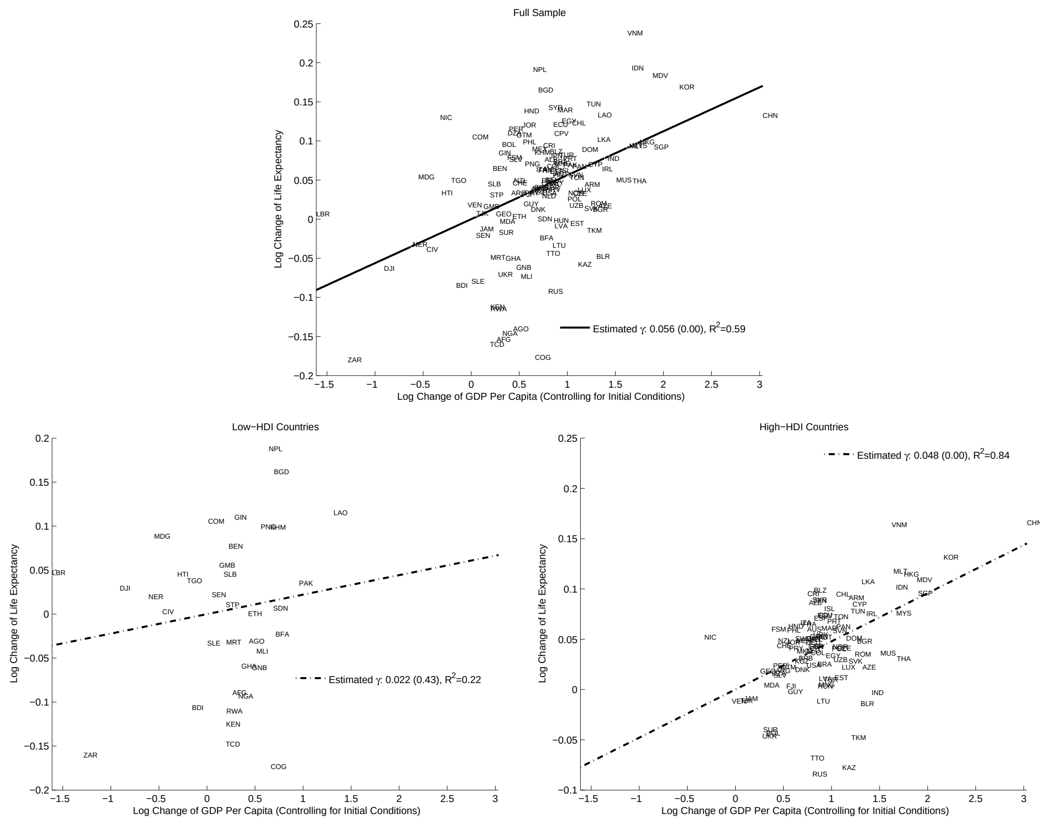


Table 3: Estimation Results for the Error Correction Model

	Preston Curve Parameters $\widehat{a}$ and $\widehat{b}$		Coefficient on Changes in per Capita Income $\widehat{\gamma_0}$	Implied Half Life Based on $\widehat{\varphi}$	R^2	N
Full Sample	3.892 (0.00)	0.051 (0.00)	0.056 (0.00)	32.8	0.59	136
Low-HDI Countries	4.802 (0.00)	−0.044 (0.64)	0.022 (0.43)	63.7	0.22	37
High-HDI Countries	3.816 (0.00)	0.054 (0.00)	0.048 (0.00)	8.2	0.84	99

Note: The table displays results from estimation of Equation (5), that is

$$\Delta llife_{i,2010} = \varphi \cdot [llife_{i,1970} - a - b \cdot lgdp_{i,1970}] + \gamma_0 \cdot \Delta lgdp_{i,2010} + v_{i,2010}.$$

The results for the levels relationship between life expectancy and per capita income broadly confirm the results from Section 2. The income elasticity of life expectancy is statistically insignificant for the low-HDI countries. Somewhat surprisingly, the long-run income elasticity is slightly larger for the high-HDI country sample than for the full sample. While the association between the change in the logarithm of life expectancy and the change in the logarithm of per capita income is (in contrast to the regression results for Equation (2)) significant for the full sample (which confirms the importance of taking into account initial deviations from the Preston curve when investigating the changes regression), once the sample is split it remains so only for the high-HDI countries.

Regarding the half lives, it is interesting to note that if a policymaker decided to foster life expectancy through economic growth, the effects on life expectancy would materialize only rather slowly, especially for the low-HDI countries: it would take around 32.8 years to remove half of the distance to the long-run value of life expectancy implied by a higher value of per capita income. Put differently, for a country with average life expectancy of 55 years (for example Botswana in 2010), according to the estimated Preston curve elasticity and half lives, a policy that leads to an increase in per capita income by 50% over 40 years (which corresponds to around 100 additional basis points of growth per year) implies an increase in life expectancy by 1.4 years in the long-run, but only by 0.6 years after 25 and 0.9 years after 50 years.

As taking into account long lags might be key to appropriately describe certain aspects of the relationship between life expectancy and per capita income (at least for the countries close to the health technology frontier), we re-run the simulations from Section 3.1 with a DGP that features an error-correction Preston curve/independent shocks mixing. Figure 15 displays the results from the Preston curve/independent shocks mixing DGP described in Section 3.1.4, an error-correction Preston curve DGP based on the error-correction model estimated in this Section, and an error-correction Preston curve/independent shocks mixing DGP. The simulated distribution of life expectancy is displayed in Figure 16.

Figure 15: Monte Carlo Results for the Error-Correction DGP

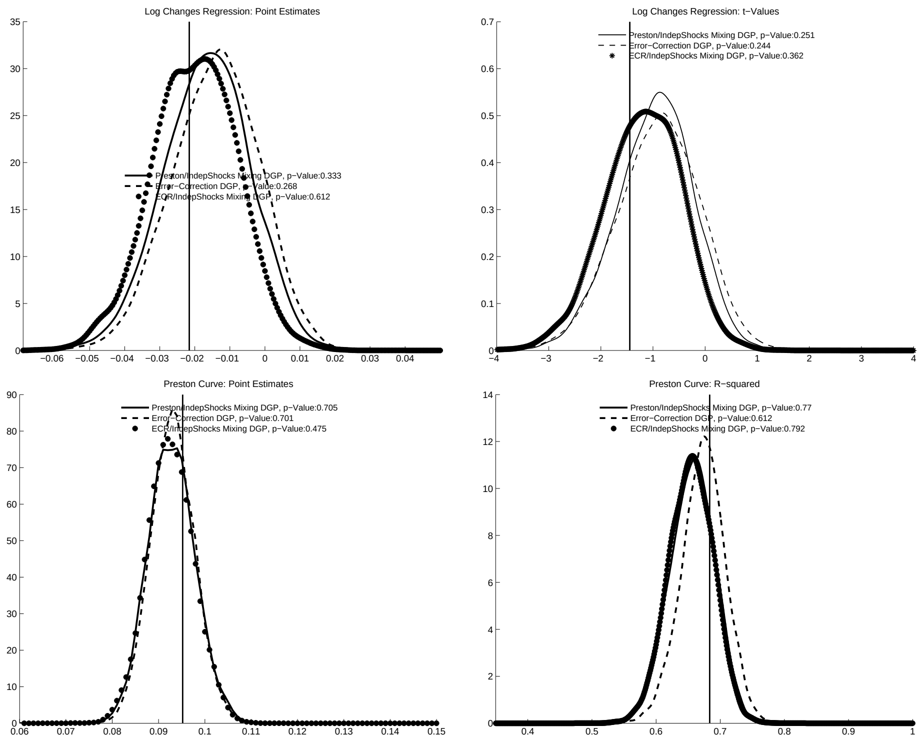
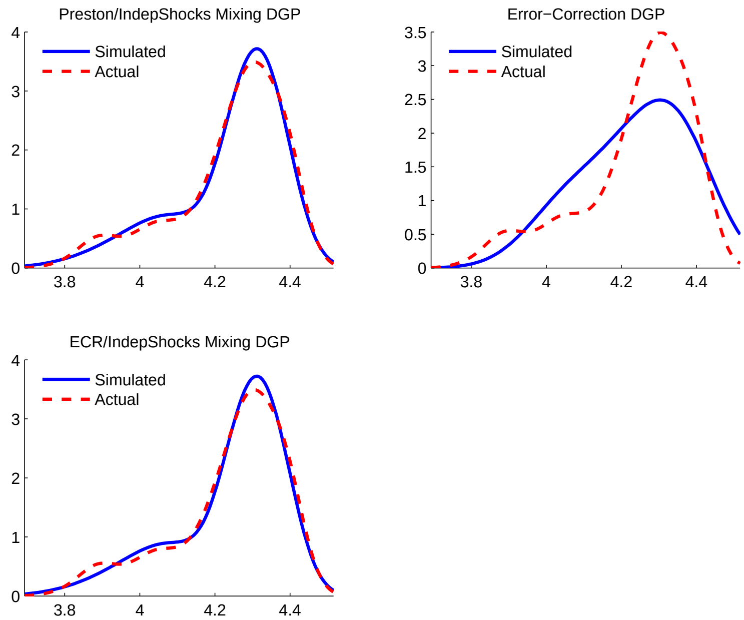


Figure 16: Cross-Sectional Distribution of Life Expectancy in 2010 for the Error-Correction DGP



While an error-correction DGP with a stable Preston curve appears to be likely to replicate the actual estimates from the Preston curve in Equation (1) and also the changes regression in Equation (2), it is unable to replicate the cross-sectional distribution of life expectancy. To produce this feature of the data, also the error-correction Preston curve DGP requires a mixing with independent shocks for low-HDI countries.[12] See also the *p*-values in Table 6.

[12]Further obvious statistics we could compute on the simulated data are the long-run Preston curve and the changes coefficient from the error-correction model. It turns out that the Preston curve/independent shocks mixing DGP, the double Preston curve DGP, the error-correction Preston curve/independent shocks mixing DGP, and the error-correction Preston curve DGP are able to replicate this statistics reasonably well.

4.2 The Evolution of the Preston Curve Elasticity Over Time

While the foregoing Section focuses on properly accounting for short-run transitional dynamics between life expectancy and per capita income, in this Section we look more closely at the corresponding long-run equilibrium relationship. To this end, we set up a truly annual ECM analogous to that in Equation (6), and allow the parameters in the level relationship between life expectancy and per capita income to vary over time. In particular, we specify

$$llife_{it} = \tau_t + \sum_{j=1}^{p} \kappa_{jt} \cdot llife_{i,t-j} + \sum_{j=0}^{q} \gamma_{jt} \cdot lgdp_{i,t-j} + u_{it}, \tag{7}$$

with $t = t_0, t_1, ..., 2010$, $t_0 = 1970 + max(p,q)$, or, written as an ECM,

$$\begin{aligned} \Delta llife_{it} &= \tau_t + \varphi_t \cdot llife_{i,t-1} + \left(\sum_{j=1}^{q} \gamma_{jt}\right) \cdot lgdp_{i,t-1} \\ &\quad + \sum_{j=1}^{p-1} \psi_{jt} \cdot \Delta llife_{i,t-j} + \sum_{j=1}^{q-1} \pi_{jt} \cdot \Delta lgdp_{i,t-j} + u_{it} \qquad (8) \\ &= \varphi_t \cdot (llife_{i,t-1} - a_t - b_t \cdot lgdp_{i,t-1}) \\ &\quad + \sum_{j=1}^{p-1} \psi_{jt} \cdot \Delta llife_{i,t-j} + \sum_{j=1}^{q-1} \pi_{jt} \cdot \Delta lgdp_{i,t-j} + u_{it}, \qquad (9) \end{aligned}$$

where $\varphi_t = \sum_{j=1}^{p} \kappa_{jt} - 1$, $a_t = -\tau_t/\varphi_t$, $b_t = -\left(\sum_{j=1}^{q} \gamma_{jt}\right)/\varphi_t$, $\psi_{jt} = -\sum_{s=j+1}^{p} \kappa_{st}$, and $\pi_{jt} = -\sum_{s=j+1}^{q} \gamma_{jt}$. The time-varying coefficients could be estimated in a state-space model framework, in which Equation (9) represents the measurement equation. For each drifting coefficient one would specify a state equation, in which the coefficient would typically evolve according to a unit root process. A computationally less burdensome approach is to approximate the evolution of the drifting coefficients by polynomials in time, that is, for example, to specify

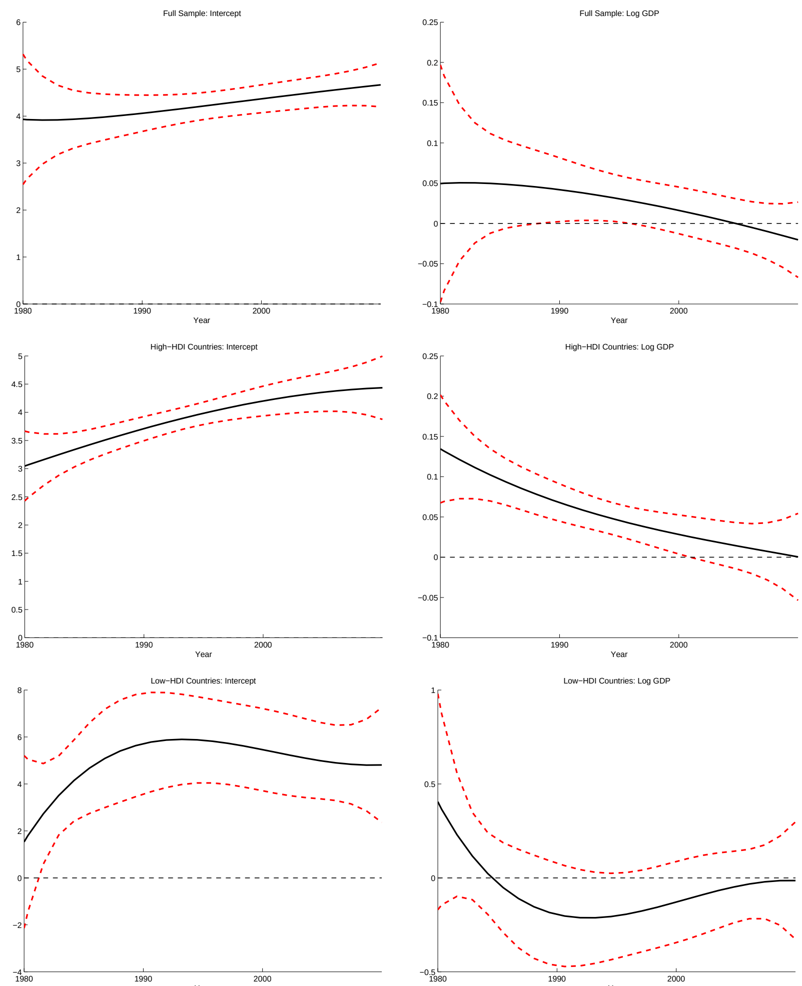
$$b_t = \sum_{j=0}^{\tau^{(b)}} \omega_j \cdot c_j(t). \tag{10}$$

We let $c_j(t)$ be Chebyshev polynomials, choose $p = q = 10$, approximate the long-run Preston curve parameters a_t and b_t by second-order polynomials in time, and the remaining short-run dynamics by first-order polynomials in time.[13] The estimation results for the long-run Preston curve parameters are reported in Figure 17.[14] The first row displays results for the full sample, and the second as well as the last for the high- and the low-HDI countries only.

[13]In fact, we estimate Equation (8) instead of (9), and we approximate φ_t as well as $\sum_{j=1}^{q} \delta_{jt}$ by first- and third-order polynomials. We then divide the polynomial for $\sum_{j=1}^{q} \delta_{jt}$ by that for φ_t to obtain the coefficients of interest a_t and b_t from Equation (9). As a result, the resulting polynomial for b_t does not necessarily look like a quadratic polynomial when plotting it. The results are robust to alternative choices of the lag and polynomial orders.

[14]We only plot the estimated functionals from 1980, as with a lag order of ten there do not remain any observations for the time period from 1970 to 1979.

Figure 17: The Evolution of the Error-Correction Preston Curve with Time-Varying Coefficients



In the full sample, the Preston curve elasticity estimates decrease over time, are not statistically significant at the beginning of the sample period and turn statistically insignificant again from the mid 1990s. When splitting the sample, the long-run Preston curve elasticity estimates remain statistically significant for the high-HDI countries only, but even for the high-HDI countries decrease over time and turn statistically insignificant from the end of the 1990s. For the low-HDI countries, the Preston curve income elasticity is not statistically significantly different from zero over the entire sample period. As in Section 4.1, the point estimates of the slope of the long-run Preston curve are slightly larger for the high-HDI countries than for the full sample; notice, however, the non-trivial extent of estimation uncertainty in Figure 17. At the minimum, the time-varying coefficients ECM suggests a substantial decline in the long-run income elasticity of life expectancy both in the full and the high-HDI country sample. Beyond that, there appears to be a high probability for the income elasticity in the Preston curve having turned statistically insignificant more recently even for the countries close to the health technology frontier.[15]

Conclusion

In this paper, we investigate the relationship between life expectancy and per capita income. We claim that the income elasticity in the standard Preston curve is likely to be overestimated due to the failure of controlling for countries' distance to the health technology frontier, and that the income elasticity of life expectancy has substantially declined even in countries close to the health technology frontier. Our results are based on simple sample splits and basic econometric techniques

[15] Similar findings are obtained when looking at the static Preston curve estimates from Equation (1) over time.

on the one hand, and a slightly more elaborate simulation exercise in which we assess the ability of different DGPs, each representing a competing theory about the importance of per capita income for the determination of life expectancy, to produce the patterns found in the actual data on the other hand.

We find that for countries far away from the health technology frontier, even though we cannot conclude with certainty, the effects of income growth on life expectancy are, relative to those of health technology adoption, close to zero. Our results thus suggest that, whether or not income can be ruled out as a determinant of life expectancy in countries far away from the health technology frontier, policymakers in developing countries should be concerned about the factors underlying their countries' delayed convergence to the health technology frontier rather than about how to most effectively spur income growth. A casual look at Figure 1 suggests that for a country far away from the health technology frontier, adopting the health technologies already in place in the countries closer to the frontier would result in an improvement of life expectancy of at least 14%. In order to achieve the same improvement in life expectancy via growth in per capita income (assuming for the moment the income elasticity estimate was statistically significantly different from zero), per capita income would have to grow by about 3200%![16] Considering that technology adoption to a large extent consists of introducing relatively inexpensive vector control measures, disseminating

[16]For large g_x the approximation $g_x = (x_1 - x_0)/x_0 \approx log(x_1) - log(x_0)$ is misleading. With an estimated income elasticity of 0.04 the log difference in per capita income a country far away from the technological frontier has to trace out in order to achieve an increase in life expectancy of 14% is 3.5. Thus, the growth in per capita income associated with an improvement in life expectancy by 14% is $exp[log(\tilde{x}) - log(x)] - 1 = exp(3.5) - 1 \approx 32$.

basic information on healthy behavior (avoiding indoor burning of solid fuels, hand washing, promoting safer sex, breastfeeding, etc.), providing sugar-salt rehydrating therapies, antibiotics, vaccinations and so on, puts into stark contrast what policymakers in developing countries can expect from policies focusing on health technology adoption vis-à-vis income-growth centered policies. For example, a package of six vaccines assembled by the World Health Organization costs less than $1, and deworming costs just 50 cents a year.[17] Enhanced accountability of local governments, a free press, empowerment and education of their people are certainly key to creating an environment conducive to the adoption of health technologies. Globalization, by facilitating the spread of technologies, ideas and behaviors, may significantly speed up this process. By supporting the flow of health technologies from developed to developing countries, international organizations such as the World Health Organization or the United Nations may also play a crucial role.

Finally, we provide evidence suggesting that even for the countries close to the health technology frontier the role of income for the determination of life expectancy has substantially weakened during the last two to three decades. Health conditions are thus becoming increasingly disconnected to per capita income in developed countries. Living a healthier life requires new insights about healthy behavior (smoking, obesity, stress, diet), their spread and adoption on a large scale. The individual's behavior thus appears to gain importance for the prolongation of life in developed countries, too.

[17] See Miguel and Kremer (2004).

A Appendix

A.1 Countries Included and Subsamples

The countries included in our baseline specification with HDRO data are:

Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bolivia, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Canada, Cape Verde, Chad, Chile, China, Colombia, Comoros, Congo, Congo (Democratic Republic of the), Costa Rica, Croatia, Cyprus, Czech Republic, Côte d'Ivoire, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Fiji, Finland, France, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, China (SAR), Hungary, Iceland, India, Indonesia, Ireland, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea (Republic of), Kyrgyzstan, Lao People's Democratic Republic, Latvia, Liberia, Lithuania, Luxembourg, Madagascar, Malaysia, Maldives, Mali, Malta, Mauritania, Mauritius, Mexico, Micronesia (Federated States of), Moldova (Republic of), Mongolia, Morocco, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russian Federation, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, Spain, Sri Lanka, Sudan, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Thailand, The former Yugoslav Republic of Macedonia, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela (Bolivarian Republic of), Viet Nam .

The high-HDI countries are:

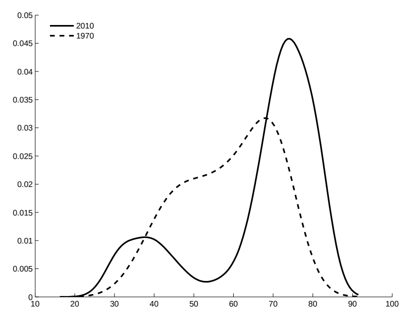
Albania, Algeria, Argentina, Armenia, Australia, Austria, Azerbaijan, Barbados, Belarus, Belgium, Belize, Bolivia, Brazil, Bulgaria, Canada, Cape Verde, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Fiji, Finland, France, Georgia, Germany, Greece, Guatemala, Guyana, Honduras, Hong Kong, China (SAR), Hungary, Iceland, India, Indonesia, Ireland, Italy, Jamaica, Japan, Jordan, Kazakhstan, Korea (Republic of), Kyrgyzstan, Latvia, Lithuania, Luxembourg, Malaysia, Maldives, Malta, Mauritius, Mexico, Micronesia (Federated States of), Moldova (Republic of), Mongolia, Morocco, Netherlands, New Zealand, Nicaragua, Norway, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russian Federation, Singapore, Slovakia, Slovenia, Spain, Sri Lanka, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Thailand, The former Yugoslav Republic of Macedonia, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela (Bolivarian Republic of), Viet Nam .

The low-HDI countries are:

Afghanistan, Angola, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Chad, Comoros, Congo, Congo (Democratic Republic of the), Côte d’Ivoire, Djibouti, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, Kenya, Lao People's Democratic Republic, Liberia, Madagascar, Mali, Mauritania, Nepal, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Sudan, Togo .

A.2 Figures

Figure 18: The Cross-Sectional Distribution of Life Expectancy When Controlling for the Sub-Saharan African Average Level of Life Expectancy



A.3 Tables

Table 4: Death and Poverty Around the World in 2002

Millions of Deaths per Year	Treatments, Prevention	World	Low-Income	High-Income
Respiratory Infections	Antibiotics	3.96	2.90	0.34
HIV/AIDS	HAART	2.78	2.14	0.02
Perinatal Deaths	Pre- and post-natal care	2.46	1.83	0.03
Diarrheal Diseases	Oral rehydration therapy	1.80	1.50	0.00
Tuberculosis	Public health: DOTS	1.57	1.09	0.01
Malaria	Partially treatable	1.27	1.24	0.00
DPT/Measles/Polio	Vaccinations	1.12	1.07	0.00
Percent of Deaths				
Ages 0 to 4		18.4	30.2	0.9
Ages 60 and Above		50.8	34.2	75.9

Note: HAART stands for Highly-active anti-retroviral therapy, perinatal deaths are deaths in the first seven days of life, and are typically associated with low birthweight, DOTS stands for directly-observed treatment short course, and is treatment combined with community monitoring to ensure full compliance, and DPT stands for diphtheria, pertussis (whooping cough) and tetanus. Low income and high income are World Bank designations and correspond (approximately) to below $5,000 and above $10,000 PPP in Figure 1. Note that the middle-income countries are not shown, so that the world figures are not the sum of the low-income and high-income figures. Figures are for 2002, are based on WHO data, and are subject to substantial margins of error. Table and note reproduced from Deaton (2007).

Table 5: p-Values

	Correlation	t-Value	Preston Curve Elasticity	R^2	Kolmogorov-Smirnov Test (p-Value)	$P\left(\widehat{\gamma} \in [\widehat{\gamma}^{(j,r)} \pm 2 \cdot std_{\widehat{\gamma}^{(j,r)}}]\right)$
Data	-0.022	-1.45	0.095	0.68		
Preston Curve DGP	0.007 $[-0.014;0.04]$	0.004 $[-0.78;2.51]$	0.064 $[0.093;0.113]$	0.104 $[0.659;0.785]$	0.003	0.46
Independent Shocks DGP	0.799 $[-0.054;-0.01]$	0.755 $[-3.52;-0.57]$	0.977 $[0.074;0.096]$	1 $[0.469;0.618]$	0.645	0.97
Preston/Independent Shocks Mixing DGP	0.333 $[-0.042;0.007]$	0.251 $[-2.5;0.42]$	0.705 $[0.083;0.104]$	0.77 $[0.585;0.725]$	0.645	0.99

Table 6: p-Values for the Double Preston Curve and the Error-Correction Model

	Correlation	t-Value	Preston Curve Elasticity	R^2	Kolmogorov-Smirnov Test (p-Value)	$P\left(\widehat{\gamma} \in [\widehat{\gamma}^{(j,r)} \pm 2 \cdot std_{\widehat{\gamma}^{(j,r)}}]\right)$
Data	-0.022	-1.45	0.095	0.68		
Double Preston DGP	0.123 [−0.031;0.015]	0.091 [−1.91;0.93]	0.574 [0.085;0.105]	0.449 [0.619;0.75]	0.36	0.94
ECR DGP	0.268 [−0.039;0.01]	0.244 [−2.54;0.61]	0.701 [0.084;0.104]	0.612 [0.603;0.739]	0.008	0.97
Double ECR Preston DGP	0.208 [−0.034;0.011]	0.17 [−2.11;0.7]	0.673 [0.083;0.103]	0.717 [0.595;0.735]	0.369	0.97
ECR/Independent Shocks DGP	0.441 [−0.045;0.003]	0.362 [−2.74;0.19]	0.722 [0.083;0.104]	0.792 [0.585;0.721]	0.645	0.99

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