

HEALTH CARE TECHNOLOGIES AND GLOBAL CONVERGENCE OF TB AND CANCER MORTALITY RATES

DEVDATTA RAY

University of Eastern Finland

ABSTRACT

Analysis of cancer and TB mortality rates with 144 and 196 countries respectively for 1970 – 2012 is done. To get more reliable picture how these rates are affected by health care technologies, health care resources and relevant socio-economic variables are added to the analysis. Methods of trend growth and convergence analysis, found in economic growth empirics, are used to analyze the effects of global catch-up of health care technologies through diffusion between more and less advanced countries. The results show that there is evidence of larger declining trend growth process in low income countries for both illnesses when compared to higher income countries. However, the speed of declining mortality rate processes has been slowing in high income countries in recent decades. Both σ - and β -convergence is found to be present for TB. Conditional β -convergence in TB is larger when HCT and socio-economic factors are added to the test models. For cancer mortality, no clear evidence of σ -convergence is found. However, when technologies and socio-economic factors are added to the β -convergence model, the convergence rates are the largest in lower income countries for both illness. Contrary to this, in 1995 – 2012, β -convergence of cancer with technologies and socio-economic variables disappear.

Keywords: sigma convergence, beta convergence, trend growth, health care technology diffusion

Cancers figure among the leading causes of morbidity and mortality worldwide, with approximately 14 million new cases and 8.2 million cancer related deaths in 2012 (WHO, 2015l). The number of new cases is expected to rise by about 70% over the next 2 decades. Around one third of cancer deaths are due to high body mass index, low fruit and vegetable intake, lack of physical activity, tobacco and alcohol use. Tobacco use is the most important risk factor for cancer causing around 20% of global cancer deaths and around 70% of global lung cancer deaths (De Martel et al., 2012). Infection with HIV substantially increases the risk of cancer such as cervical cancer. Cancer can be reduced and controlled by implementing evidence based strategies for cancer prevention, early detection of cancer and management of patients with cancer (WHO, 2015l). At every stage, e.g., early diagnosis, screening, treatment and palliative care health care technologies (HCT) are used.

Tuberculosis is caused by the bacteria *Mycobacterium tuberculosis* and is second only to HIV/AIDS as the greatest killer worldwide due to a single infectious agent. In 2013, 9 million people fell ill with TB and 1.5 million died from the disease (WHO, 2015a). Globally in 2013, an estimate of 480,000 people developed multidrug resistant TB (MDR-TB) (WHO, 2015a). BCG vaccine continues to be inadequate but certainly a big step towards prevention of the illness (Zwerling et al., 2011). Between 2000 and 2013, an estimated 37 million lives were saved through TB diagnosis and treatment with the help of HCTs (WHO, 2015a). Radio therapy equipments, MRI and CT scanners all help in diagnosis, treatment and cure as in the case of cancer.

The development and possible convergence of rate of bad health outcomes (like cancer and tuberculosis mortality) across different countries over time seems to be neglected topic in health economics. If the spread of

mortality rates across the countries decreases in time, then some convergence happens between the countries. Likewise, if the absolute growth rates of declining mortality rates are larger in poor countries compared to rich ones, then the levels of mortality rates in poor countries will eventually reach the levels of rich countries. We argue that convergence is most likely an indication of global diffusion and efficient use of HCTs between the countries. In this sense different metrics of convergence are important in showing the long run trends in disease mortality rates between the countries.

This paper gives implicit results on HS convergence as affected by usages of HCT globally and attempts to validate the global catch up hypothesis caused by HCT diffusion. The target is test for convergence and to show impacts of HCT on cancer and TB mortality in different GNI per capita level countries. We defend the idea that the poorest countries can quite quickly adopt improvements in their HS if they can afford and get access to technological advances found in rich countries. The social inequalities and the low level of health expenditures in non-rich countries however slower this important and urgently needed catch-up. To get more reliable picture how cancer and TB mortality rates are affected by HCT, other health care resources and relevant socio- economic variables like total health expenditure per capita, GNI per capita, proportion of population using improved sanitation facilities-total, adult alcohol consumption, and share of regular daily smokers in the population are added to in to analysis.

The paper is organized as follows. The next section elucidates on existing research. The section thereafter gives the data, models, and the methods used, followed by the section that reports the results. The last section concludes the paper with a discussion.

EARLIER LITERATURE

Technology And Health

Technology is a crucial ingredient of health care. BJM defines technology as any intervention which influences health and society (Berger, 1999). In response two trends are observed during the latter half of the twentieth century. First, there is a rising trend in health expenditure. Second, patients survive globally major illnesses like cancer and TB to live long. The combination of technological improvements in medical treatment and rising incomes is the driving force behind these two trends.

Technological innovation has yielded remarkable advances in health care. Breakthroughs in a variety of areas have improved health care delivery and patient outcomes. However, the proliferation of HCT and its expanding uses have contributed to increasing health care costs and the former has often been cited as a culprit for the latter. However, this relationship is variable, complex and evolving (Newhouse, 1992). Creation and development of new technologies are driven by both demand and supply side forces.

There are many benefits of HCT innovations. The most important is the value of better health, i.e. longer life as well as improved quality of life after early and/or proper diagnosis of illnesses like TB and cancer. A second benefit of HCT innovation is its effect on income formation. One part of this benefit is an increase in production that results from technology allowing people to work and earn more. Offsetting this productivity benefit are the medical and nonmedical costs of additional years of life. The net value of medical technology change is the difference between the benefits and costs (Cutler & McClellan, 2001). A positive net value implies that the technological change is worth it in total.

A variety of factors may influence health over time, of which medical technology is only one. It is widely accepted that technological change has accounted for the bulk of medical care cost increases over time (Cutler & McClellan, 2001). Technological change is bad only if the cost increases are greater than the benefits that technological change brings about. Cutler et al. (2001) reported on a series of studies that examined the costs and benefits of medical technology changes. These studies showed that medical spending as a whole was worth the increased cost of care. HCT change affects treatments in two ways, namely, treatment substitution and treatment expansion. HCT could be expensive, but it still could be worth paying for, if it extended the length or quality of life or otherwise resulted in positive social returns. So, understanding cost effectiveness is more important than understanding costs alone.

The paper by Sorenson, Drummond and Khan (2013) critically appraises this conjecture the existing literature with the aim of offering a more detailed analysis of the relationship between HCT diffusion and health expenditure. Selected 86 articles are reviewed and relevant information is extracted into a standardized template and analyzed for key cross-cutting themes, e.g., impact of technology on costs, factors influencing this relationship and methodological challenges in measuring such linkages etc. Based on their analysis, they argue that attention also needs to be focused on exploring whether investments in medical technology result in better value as measured by therapeutic benefits, cost effectiveness, and other important health outcomes and under which conditions technologies allow for the most effective and efficient use of available health care resources.

If the new HCT supplements the existing instrumentation and its purpose is to expand the treatment into the conditions that have not been treated previously

due to scientific (as the methods of treatment were unknown) or economic (as the methods of treatment were known, but enormous costs made it unfeasible on a larger scale) reasons, one can say that it could have a cost increasing effect (expansion effect). On the other hand, extra savings may be expected if a decrease in the relative price of a given type of treatment (due to e.g. the introduction of a new technology) reduces the use of other, more expensive substitute types of care (substitution effect).

Some technologies may improve the efficiency of care delivery by reducing procedure time, length of stay or number of hospitalizations, thereby increasing the capacity of the hospital to treat additional patients. Overall costs may rise as a result, but such outlays will likely result in improved health outcomes for a greater number of patients. Technological advancements may generate consumer demand for care (and, perhaps more intense, costly services, even if not cost-effective), and demand for insurance (Sorenson et al. 2013).

Past literature reviews imply that HCT diffusion is an important contributor to improved health status as measured by life expectancy and mortality rates. Preston (1996) and Soares (2005) argued that increases in life expectancy have occurred independently of increases in per capita income. While not denying the importance of other factors, Soares (2005) placed emphasis on changes in mortality determined from technological innovations in medical and biological sciences. Both authors give evidence that the positive cross-sectional relationship between life expectancy and per capita income had shifted upward steadily over time. Kremer (2002) emphasized the importance of modern medical technologies in allowing tremendous improvements in health even at low income levels. Jamison, Sandbu and Wang (2001) documented the importance of different rates of technological progress

across countries for the declining cross- country variation in infant mortality rates. Becker, Philipson and Soares (2005) argued that in the last 50 years, countries starting with modest longevity levels experienced life expectancy gains significantly larger than countries starting with high longevity thresholds. They attributed the convergence in life expectancy in large part to the diffusion of existing knowledge that had helped reduce mortality from major diseases. Fogel (1994) referred to a potential explanation for the acceleration of life expectancy improvements in the huge social investments made in biomedical research in most developed countries, whose payoffs were not counted in some of them as part of national income in the past, even though they produced a large stream of benefits during in the past decades. Preston (1996) suggested also that mortality changes in developing countries came about through the provision of public programs and the dissemination of knowledge.

Baltagi, Moscone and Tosetti (2011) modeled differences across OECD countries in health productivity as a function of traditional factor inputs, life styles conditions and technological progress. The authors first explored available data on medical technology to explain health productivity in the OECD countries. Baltagi et al. (2011) assumed that technology was unobserved and hence used proxy for it by means of a spatial process. Baltagi et al. (2011) like Ertur and Koch (2007) allowed technological progress in a country to be related to the technology adopted by neighboring countries. That technology could show a geographical pattern had earlier studied by Keller (2004). In the medical literature, a consolidated body of research supported long-ago the important role of interpersonal communication and social networks in the diffusion of medical technologies (Coleman, Katz & Menzel, 1966). Again, Baltagi et al. (2011) like Birke (2009) chose a survey on the role of

social networks in explaining individual choices in a large variety of economic, social and health behavior. Papageorgiou, Savvides and Zachariadis (2007) studied the impact of a set of measures of international medical technology diffusion on health status and concluded that technology diffusion is an important determinant of improved health status and mortality rates. Their data was on 63 countries over the period 1961 to 1995.

Technology Diffusion And Health Convergence

Literature shows that medical innovation diffuses steadily across the world contributing to significant improvements in life expectancy. International medical diffusion occurs through two distinct channels. Firstly, imports of medical goods, such as drugs, vaccines and medical equipment. Papageorgiou et al. (2007), Caselli and Wilson (2004), and Eaton and Kortum (2001) 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. Secondly, through the direct flow of medical knowledge from a few frontier countries to the rest of the world, a flow that is facilitated by information networks created by medical students from non-frontier countries who study in frontier ones (Papageorgiou et al., 2007).

Above remarks mean that HTC is a major factor in explaining the differences in countries HS and in possible HS convergence between them. The theoretical basis of economic convergence is derived from the neoclassical growth model which gives the result that in the long run all countries move towards a common steady state level of income per capita because of decreasing marginal product of capital, i.e. the steady state is obtained under certain conditions. Thus, convergence is closely connected to the long term (economic) growth. In case of long fun mortality rates, one would expect convergence of the HSs due to the

existence of upper bounds of many health indicators as well as due to diminishing returns of inputs, e.g. health expenditures, efforts in education, economic development (Gächter & Theurl, 2011). A number of methods are proposed to study the question of convergence.

In σ – convergence cross sectional standard deviation or coefficient of variation (or some other measure of variability) of a variable across a group of homogenous countries decreases over time. As standard deviation is a measure of the spread of data and is defined as a numerical measure of the average variability of around the mean. If its value diminishes with successive measures over time, this will support the hypothesis of convergence (Nixon, 2000). In order to statistically test for σ - convergence it is necessary e.g. to analyze the trend of standard deviation values in the data over successive points of time.

The disadvantage of σ - convergence is that it may be disproportionately influenced by discontinuities, outliers and short run shocks. Additionally, the existence of a diminution of standard deviation or coefficient of variation does not confirm that a country approaching the sample mean will remain there. The second approach limits these shortcomings, positing that convergence exists if a poor economy tends to grow at a faster (but diminishing) rate than a rich one. Now the poor country tends to catch up the rich country. This property corresponds to the concept known as β - convergence or regression to the mean (Barro and Sala-i-Martin, 1992a; Sala-i-Martin, 1996 & Boyle & McCarthy, 1997). Within this method of analysis two forms of convergence are distinguished, namely, unconditional or absolute and conditional rates of growth.

By convergence literature, economists typically refer to the large literature, typified by the seminal papers by Baumol (1986), Barro and Sala-i-Martin (1992b) and Mankiw, Romer and Weil (1992), exploring β - convergence. Sala-i-Martin (1996) surveying this literature,

concluded that the estimated speeds of β -convergence are so surprisingly similar across cross-sectional data sets, that one can say that economies close the gap between present levels of income and balanced growth levels by, on average, 2% annually. Past panel data studies find even higher rates of β -convergence (Evans, 1997), as do the county-level U.S. studies of Higgins, Levy and Young (2006) and Young, Higgins and Levy (2013). Despite the literature's stress on β - convergence, economists have acknowledged that it is not a sufficient condition for σ -convergence (Barro & Sala-i-Martin, 1992b). Quah (1993) and Friedman (1992) both suggested that σ -convergence should be of greater interest because it speaks directly as to whether the distribution of income across economies was becoming more equitable.

The underlying principles of the neoclassical growth model have applicability to the study of convergence in health care expenditure as there is a strong correlation between the latter and GDP income (Nixon, 2000). His findings provide statistically significant evidence for β -convergence in GDP and this is a driver of the results of health expenditure convergence. The results of Nixon (2000) show that statistically significant σ -convergence in health care expenditure outcomes occurred in the present countries of the EU over the period 1960-95 and in 1980-95 for β - convergence. The analyses reveal a common trend in that Southern European OECD countries which have generally exhibited convergence towards the mean in health expenditure and convergence towards the EU mean in for health outcomes.

Previous studies before Clark (2011) generally concluded that a nation's level of economic development and /or its growth rate were positively associated with improvements in human welfare, particularly among less developed countries. However, other works suggested that economic growth might not have played a large role in

mortality improvements during the twentieth century. Research showed that economic growth produced only modest welfare benefits in the developing world. Indeed, even when economic development was found to significantly improve a country's infant survival rate, child survival rate or life expectancy among developing countries, it often produced effects that were smaller than other predictors, such as education or gender-related measures.

In his study, Clark offered new evidence regarding (a) inequality trends in life expectancy and infant mortality, as well as (b) the role that economic development may have played in producing these trends (Clark, 2011). He first examined whether life expectancy averages and infant mortality rates converged across 195 countries during the 1955 - 2005 period. Consistent with prior work, he found that cross-national inequality in life expectancy declined during the 1955 - 2005 period, but that this convergence stalled during the post- 1990 era. Moreover, and contrary to previous work, he found that infant mortality rates diverged continuously across the sample period. He then developed a narrative to explain these contrasting trends, suggesting that cross-national health outcomes followed a welfare Kuznets curve. He also estimated the differential impact of economic development on life expectancy and infant mortality. According to this model, economic development improved life expectancy more than it reduced infant mortality among poor countries, whereas the situation was reversed among wealthier nations. In sum, Clark (2011) argued that economic development had contributed to both convergence in life expectancy and divergence in infant mortality.

Moser, Shkolnikov and Leon (2005) investigated to what extent worldwide improvements in mortality over the past 50 years have been accompanied by convergence in the mortality experience of the world's population. The

global mortality distribution at a point in time was quantified using a dispersion measure of mortality (DMM). Trends in the DMM indicated global mortality convergence and divergence. Their analysis used United Nations data for 1950-2000 for all 152 countries with populations of at least 1 million in 2000 (99.7% of the world's population in 2000). DMM for life expectancy at birth declined until the late 1980s but increased since then, showing a shift from global convergence to divergence. In contrast, the DMM for infant mortality indicates continued to converge since 1950. They concluded that the shift from global convergence to divergence was being driven by reversals in adult mortality. With respect to the former Soviet Union, including the Russian Federation, there was strong evidence that the reversals in life expectancy at birth were almost exclusively due to increases in adult mortality. So, based on the research by Moser et al. (2005) one could say that although in one sense the world became a better place as mortality declined, in another way it became worse as the distribution of life expectancy at birth worldwide started to diverge.

Health is an important dimension of welfare comparisons across individuals, regions and states. Particularly from a long-term perspective, within country convergence of the health status has not been that often investigated. Gächter and Theurl (2011) in their research studied the relation between initial levels of the health status and its improvement at the local community level in Austria in the time period 1969-2004. Method wise they used age standardized mortality rates from 2381 Austrian communities as an indicator for the health status and analyzed the convergence/ divergence of overall mortality for (i) the whole population, (ii) females, (iii) males and (iv) the gender mortality gap. Convergence and divergence was studied by applying different concepts of cross regional inequality, namely, weighted standard deviation, coefficient of variation and Theil coefficient of inequality.

The researchers used weighted OLS, quantile regression and Kendall's rank concordance to test for absolute and conditional β - convergence in mortality. They found mixed results with reference to σ - convergence, while the weighted standard deviation indicated an increase in equality for all four variables, the picture appeared less clear when correcting for the decreasing mean in the distribution.

However, they found highly significant coefficients for absolute and conditional β -convergence between the periods. While these results were confirmed by several robustness tests, they also found evidence for the existence of convergence clubs. In order to test for differences in the β - coefficients within the distribution the authors also ran quantile regressions for the lower and upper quartile of the distribution. Once again, the impression of divergences in the β - coefficients in different parts of the distribution was confirmed, albeit the conclusion of β - convergence across communities is unaffected by this result.

Goli and Arokiasamy (2014) did testing of the convergence hypothesis for trends in maternal and child mortality indicators during 1990 to 2008 by using three different types of convergence metrics. They found discrepancies in the progress achieved in terms of Millennium Development Goals (MDG) namely, for MDG 4 (reduce child mortality) and MDG 5 (improve maternal health). Graphical assessment indicated clear evidence of catching-up process for all the maternal and child mortality indicators, but the β - convergence model estimates showed lack of convergence. The results of the absolute β - convergence estimates suggested a divergence in the progress of the Maternal Mortality Ratio (MMR) across the countries for the entire period and convergence for the recent period. The progress in all child mortality indicators was β - divergent. Such divergence increased subsequently.

The past and current research on mortality and birth rates, and on life expectancy have shown that convergence is a vital and important concept in analysis of population health across the countries in long run (Gächter et al., 2011 for additional references). The concepts of σ - and β - convergence play here an important role and they give the unifying standard also for the global mortality rate analysis.

DATA, MODELS AND METHODS

Data

Panel data for countries are obtained for 43 years (1970-2012). The first study variable is TB mortality/100,000 persons including HIV positive cases (TBM_{kt}) for 196 countries. The second is cancer mortality/100,000 persons (CM_{kt}) and includes summation of deaths caused by 24 types of cancer in 144 different countries. Health technology variables (HCT's) include radio-therapy equipment, mammography machines, magnetic resonance imaging (MRI) units, computed tomography (CT) scanners, all in terms of per 1000, 000 inhabitants, BCG vaccines in terms of % of live births who received it, doctors working in any medical field (including oncologists) per 1000 people, and hospital beds/1000 patients besides health expenditure variables for OECD and other countries in per capita and in % of GNI per capita terms. The socioeconomic variables included in study are kilocalories per person in-take per day, alcohol consumption in liters of pure alcohol per person per year, % of regular daily smokers in the population, % of population using improved drinking water source, and proportion of population using improved sanitation facilities.

The differentiation of the countries into 4 groups was done by their income levels using the World Bank's Atlas method (using current US \$). Group 1 (low income

economies) consist of countries which have a GNI per capita of \$1045 or less. 30 countries fall into this category. Group 2 (lower middle-income economies, 49 countries) refers to GNI per capita of \$1046 - \$4125. The third category or group 3 (upper middle-income economies) has 55 countries with a GNI per capita of \$4126 - \$12735. Group 4 (high income economies, 62 countries) has a GNI per capita in the range of \$12736. The data sources are given in details in Appendix A). Note that we analyze periods 1970 – 2012 and 1995 – 2012 separately because in years 1970 -1995 the mortality rates in many countries were not measured with high precision.

Models and Methods

Trend growth models. Elementary growth analysis is built on trend model presentation like

$$y_t = a \exp(b_1 T + b_2 T^2) \quad (1)$$

where a refers to the starting value of process and coefficients b_1 and b_2 measure the growth rate and the acceleration of growth process. When analyzing the time evolution of TB and cancer mortality rates we expect growth rates to be negative with enforcing acceleration, i.e. $b_1 < 0$ and $b_2 < 0$, if mortality rates are decreasing effectively. Taking logarithms of 1) gives a linear model

$$\ln y_t = a_0 + b_1 T + b_2 T^2$$

(2)

that is easily estimated with OLS-methods. However, when the model is casts in the panel data framework like cross-section fixed effect (FE) model

$$\ln y_{i,t} = a_{i,0} + b_1 T + b_2 T^2 + \varepsilon_{i,t}$$

(3)

some estimation and inference challenges have to be solved. First, mortality rates are expected to be smooth and slowly evolving series making the error term in model 3 to

be highly auto correlated. Second, mortality rates are very country specific (i.e. clustered) even with-in same income level groups. Finally, the trend variables T and T^2 are highly collinear. All these symptoms make the statistical inference to be non-standard. We do not try handle the first problem because we need to use quite complicated bootstrap methods to derive sample valid standard errors (Vogelsang, 1998 & Linden, 2002). Note, however, that FE-OLS coefficients are still consistent and unbiased. The second problem can be corrected with weighed estimation by using cross-section weights. Finally, the last problem can be solved by estimating following two models:

$$\begin{aligned} \ln y_{i,t} &= a_{i,0} + b_1 T + \varepsilon_{i,t}, \\ \Delta \ln y_{i,t} &= b_{i,1} + b_2^* T + \varepsilon_{i,t}^* \end{aligned} \quad \text{and} \quad (4)$$

where $b_2^* = 2 \times b_2$ and $\varepsilon_{i,t}^* = \Delta \varepsilon_{i,t}$. Note that we allow in the second equation for country specific accelerations to be present in model. This model has standard properties as $\varepsilon_{i,t}^*$ are expected to be not auto correlated. However, both heteroskedastic and clustered errors are still present. Hence the model is estimated with country specific weights and with White's HSCE –corrections.

The outlined model alternatives help us to analyze if the growth process between the different income level country groups are different. For example, is estimates for b_1 and b_2 are larger in absolute terms for low-income countries than for high-income countries we have evidence of global catch-up of mortality rates.

σ – and β convergence. Following Sala-i-Martin's (1996) example, Young, Higgins and Levy (2008) assume that β -convergence holds for a group of homogeneous economies. Thus, the path natural log-income of the i th economy can be approximated by

$$\ln y_{it} = a + (1 + \beta) \ln y_{it-1} + u_{it}$$

(5)

where $-1 < \beta < 0$. The error term u_{it} is independent over t and i , and has mean zero and finite variance σ_u^2 . Because a is assumed to be constant across economies, steady state growth rates are identical, but economies can have different growth paths, depending on their initial states, to it. This is the case of unconditional or absolute β - convergence, i.e. average growth rates of poor economies are unambiguously greater than those of rich economies because of higher marginal product of capital or because of global catch-up effects. Allowing for heterogeneity across the economies ($a_i \neq a_j$), $-1 < \beta < 0$ would imply the case of conditional or relative β -convergence. The average growth rate of an economy is an increasing function of its distance from its own steady state growth level of income. This is a weaker case of β - convergence and increases the set of possible scenarios where it does not imply σ - convergence.

To analyze the relation between σ - and β - convergences, by arranging the above equation (5) one gets

$$\ln\left(\frac{y_{it}}{\ln y_{it-1}}\right) = a + \beta \ln y_{it-1} + u_{it}$$

(6)

Thus, $\beta < 0$ implies a negative correlation between income growth and initial log income. The sample variance of log income in t is given by

$$\sigma_t^2 = \frac{1}{N} \sum_{i=1}^N (\ln y_{it} - \mu_t)^2$$

where μ_t is the sample mean of (log) income at time t . The sample variance is close to the population variance when N is large, and equation (5) can be used to derive the evolution of σ_t^2 :

$$\sigma_t^2 = (1 + \beta)^2 \sigma_{t-1}^2 + \sigma_u^2$$

Only if $-1 < \beta < 0$ is this *difference equation* stable, so β -convergence is necessary for σ -convergence. If $\beta \geq 0$, the variance increases over time. If $\beta = 0$, the variance is constant (full convergence), and if $\beta < -1$, log of income would oscillate potentially from positive to negative values and back (making little economic sense).

Moreover, as $(1 + \beta) < 1$, the approach to stable σ^2 value is monotonic. Economies can be β -converging toward one another while, at the same time, random shocks are pushing them apart. Despite β -convergence, if the initial dispersion of income levels is, by chance, small relative to the variance of random shocks then the dispersion of incomes will converge toward its steady-state value from below. Note in equation (6) above parameter β governs the speed at which the variance approaches its steady-state value because, according to the equation (5), it governs how long the effect of shocks persist.

Conditional β -convergence does not imply σ -convergence arise. In empirical applications the country specific factors (a_i 's) are often modeled as linear functions of various economic and/or socio-demographic variables. Intuitively, consider two economies, A and B, where both economies begin at the same level of income. However, assume that B begins on its balanced growth path while A begins far below its balanced growth path, and assume that β -convergence holds. The initial variance σ_0^2 will be zero, but σ_t^2 will grow over time as A grows faster than B and approaches a higher balanced growth path. Indeed, β -convergence is the reason for the increasing variance. In

real economies, σ -convergence would also depend on whether or not disturbances are correlated and have constant variances across time and economies.

Next, we first analyze convergence with trend models and then with σ - and unconditional β -convergence models for our sample countries for TB and cancer mortality in year 1970 - 2012. We calculate estimates for different income group countries (i.e. the convergence clubs). To get a detailed picture of global differences in TB and cancer mortality we use also the distribution sensitive estimation approach, i.e. the quantile regression. Different quantile process coefficients related to the levels of cancer and TB mortality will be analyzed. After this we turn more specifically on conditional β -convergence allowing initial levels of variables of health technology (HTC) and socio-economic variables to affect the convergence.

RESULTS

TB mortality

Trend estimates. Table 1 depicts the results of models

$$A_1 : \quad \ln y_{i,t} = a_{i,0} + b_1 T + \varepsilon_{i,t}$$

$$A_2 : \quad \Delta \ln y_{i,t} = b_{i,1} + b_2^* T + \varepsilon_{i,t}^*$$

We observe (see Table 1) that for low and lower middle-income countries the trend growth estimates are largest (in absolute terms). We report results with countries on periods 1970 – 2012 and 1995 – 2012 separately because in years 1970 – 1995 the TB mortality rates in many countries were not measured with high precision. The estimates are 1.5-2.0 times larger than for high-income countries. For TB in Table 1 the acceleration estimates

(b_2 's) are negative for low, lower middle and upper middle-income countries showing that speed of decreasing TB-mortality rates is increasing. Contrary to this in high income countries we find haltering-up. Note that t -values for level models are only indicative.

Table 1.
Trend model estimates of TB mortality rates 1970 – 2012 and 1995-2012

MODEL	Low income N = 90	Lower middle income N = 49	Upper middle income N = 55	High income N = 62
$A_{1,1970-2012}:$ b_1	-0.030 (-47.87)	-0.026 (-66.27)	-0.019 (-66.72)	-0.020 (-93.83)
$A_{2,1970-2012}:$ b_2	-0.00065 (-5.39)	-0.00041 (-5.67)	-0.00009 (-1.21)	0.0001 (1.42)
$A_{1,1995-2012}:$ b_1	-0.042 (-35.70)	-0.033 (-53.55)	-0.027 (-42.19)	-0.022 (-41.28)
$A_{2,1995-2012}:$ b_2	-0.0042 (-15.30)	-0.0029 (-12.93)	-0.00007 (-0.45)	0.00056 (2.49)

σ –convergence. In the framework of σ – convergence the Figure 1 below shows a very clear convergence from 1970's to early 1990's in the upper and lower middle in economies for TB mortality. Till about the 1990s all the four country groups have a downward slope in yearly cross-section SD's showing a σ – converging trend. Thereafter they diverged but new convergence paths were found next at the end of century. Subsequently, especially the low and the high-income countries had a downward slope in σ – convergence trend.

Figure 1.
 σ – convergence 1970 – 2012

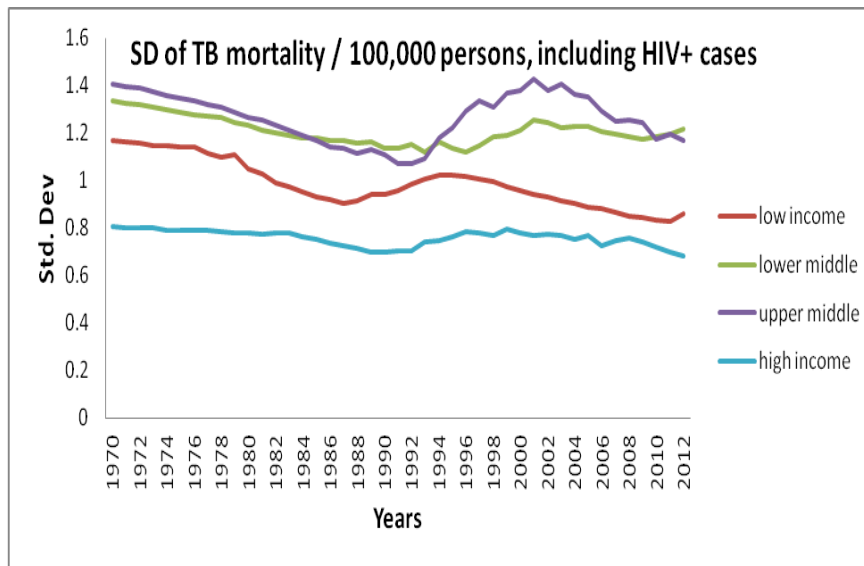
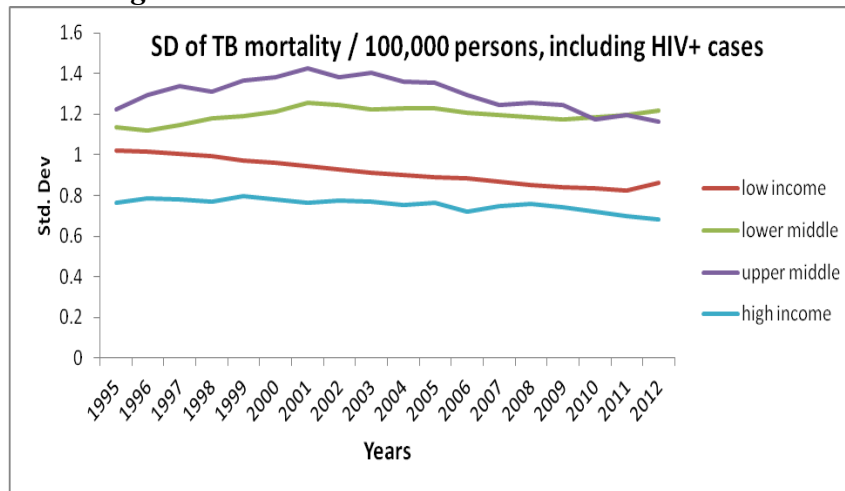


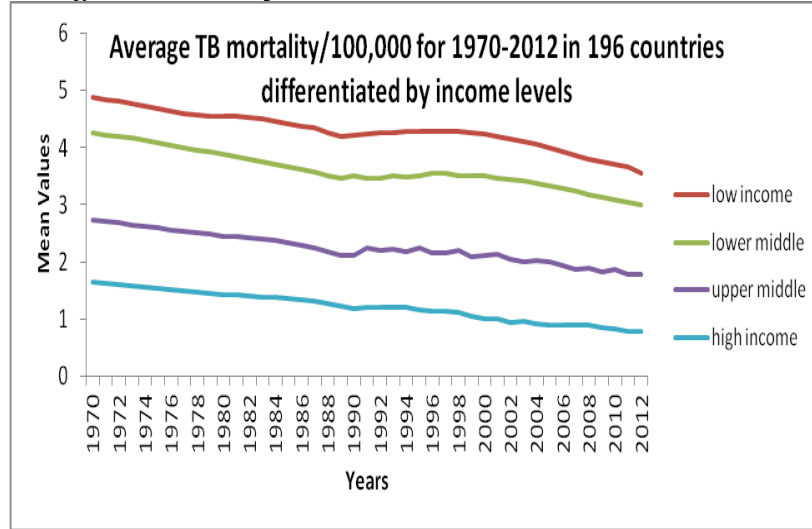
Figure 2.
 σ – convergence 1995 – 2012



The upper middle-income countries register higher SD values than the other groupings (Figure 2). These are a disparate group including former Warsaw Pact countries. Since becoming independent many of these countries have undergone various economic transformation and subsidies in the health sector have been eliminated or reduced. Further HCT is not always readily available as in high income countries due to lower total health expenditure per capita and institutional bottlenecks (Rechel et al., 2014). R & D expenditure is also less than in high income countries. The outcome of all these are revealed in high incidence of TB mortality. This group also has other countries following the Soviet style economic policies. Since the breakdown of former Soviet Union many have been embroiled in problems in the health sector as one witnessed in former Warsaw pact countries.

The average of TB mortality is seen to be going down for all income group over the years (Figure 3) suggesting the number of cases per year is going down too in all the 196 countries (Appendix B gives the growth rates between periods 2012 and 1970 and 2012 and 1995 for different income groups). The best scenario is seen in the high-income countries and comparatively the worst one is observed in the low-income economies. There is a tendency for intersection for the low income and the lower middle economies in the years after 2012 suggesting possible convergence if the low-income countries continue their catching up with lower middle-income countries with regards to TB mortality convergence (see Figures 1 and 2).

Figure 3.
Average TB mortality 1970 – 2012



β – convergence: cross section approach. We derive the unconditional β - convergence results with cross section by estimating the following model with OLS- and Quantile estimation methods

$$\ln\left(\frac{y_{i,t}}{y_{i,t_0}}\right) = \alpha + \beta \ln y_{i,t_0} + u_i.$$

(A)

Now $\beta < 0$ implies a negative correlation between log of mortality growth and initial log of mortality rate. It should be noted that this so-called Barro regression is a difference equation that converges to stable solution when $-1 < \beta < 0$ and the convergence is faster when β is closer to -1 .

Next, we specify conditional β – convergence with technology variables, i.e. the initial level t_0 (year 1970 or 1995) HTC variables that may have their own impact on the change rate on TB and cancer mortality rates. Thus, we

allow HTC –variables condition the initial level convergence, i.e. the speed of convergence measured with β parameter

$$\ln\left(\frac{y_{i,t}}{y_{i,t_0}}\right) = \alpha + \beta \ln y_{i,t_0} + \mathbf{v}' \mathbf{X}_{i,t_0}^{TECH} + u_i.$$

(B)

For period t_0 the technological variables $\mathbf{X}_{i,t_0}^{TECH}$ include:

$HCTC1_{kt}$: radiotherapy equipment per 1000,000 inhabitants

$HCTC2_{kt}$: total mammography machines - total in hospitals and in ambulatory care providers per 1000,000 inhabitants)

$HCTC3_{kt}$: magnetic resonance imaging (MRI) units per 1000.000 inhabitants and includes MRI

units in hospitals and ambulatory care providers,

$HCTC4_{kt}$: computed tomography (CT) scanners, total per 1000,000 inhabitants (includes

hospitals and ambulatory care providers),

I_{kt} : BCG vaccine in terms of % of live births,

DOC_{kt} : doctors working in any medical field/000 people, and

$HOSB_{kt}$: hospital beds/1000 patients,

RD_{kt} : R & D expenditure as a % of GDP.

Contrary to this model we assume next that the socio-economic factors condition the convergence,

$$\ln\left(\frac{y_{i,t}}{y_{i,t_0}}\right) = \alpha + \beta \ln y_{i,t_0} + \mathbf{\delta}' \mathbf{X}_{i,t_0}^{SOC} + u_i.$$

(C)

For period t_0 the technological variables $\mathbf{X}_{i,t_0}^{SOC}$ include:

$THEXPC_{kt}$: total health expenditure per capita (PPP, constant 2011 international \$),

$GNIPC_{kt}$: GNI per capita calculated using the World Bank Atlas method (current US \$),

FS_{kt} : food supply: kilocalories per person per day,

AW_{kt} : % of population using improved drinking water source,

ISA_{kt} : proportion of population using improved sanitation facilities-total,

AC_{kt} : alcohol consumption/adult (15+) in liters of pure alcohol per person per year and,

TP_{kt} : % of regular daily smokers in the population 15 + years.

Finally, we combine both the technical and the socioeconomic indicators in one model:

$$\ln\left(\frac{y_{i,t}}{y_{i,t_0}}\right) = \alpha + \beta \ln y_{i,t_0} + \boldsymbol{\nu}' \mathbf{X}_{i,t_0}^{TECH} + \boldsymbol{\delta}' \mathbf{X}_{i,t_0}^{SOC} + u_i$$

(D) All the cross-section OLS regressions t -values were estimated with White–diagonal variance corrections because residual heteroscedasticity and non-normality were found in the residuals diagnostics. The final estimation equations contained only variables having 5% level significant coefficient values and variables causing multicollinearity were excluded. We don't report the estimated values of $\boldsymbol{\nu}$ and $\boldsymbol{\delta}$ because our focus is on the convergence parameter β and how it is affected by the presence of control variables. The detailed estimation results are provided by request from the authors. Thus Tables 3 and 4 (below) reports the estimation results only on the speed of convergence (the size of β) from models B, C, and D. Interestingly, β –convergence increases as we add new variables in to model. This is true to all country groups except for the low and the upper middle-income countries in years 1970 – 2012 and for lower middle-income countries in years 1995 – 2012.

We argue that this “speeding up” phenomena is a result starting values of variables included in X_{i,t_0}^{TECH} and X_{i,t_0}^{SOC} . More favorable is the initial level of these variable faster is the convergence. We notice that the socio-economic variables (model C) make a somewhat greater effect to the convergence compared to the technology variables (model B). However, the combined model D) provides the largest speed-ups especially in years 1995-2012 for some country groups. However, these results are less warranted when observe that the quantile estimation does not fully support the OLS –estimation results above. The absolute size of β increases also in median estimation (in Tables 3 and 4) with variable addition, but not so much as in OLS estimation.

Table 2.
Cross section estimates of convergence parameter β with models’ A - D: 1970 – 2012

MODEL	Low income N = 90	Lower middle income N = 49	Upper middle income N = 55	High income N = 62	Total (median regression) N = 196
A	-0.612 (-5.56)	-0.360 (-3.97)	-0.346 (-4.59)	-0.406 (-3.64)	-0.281 (-8.06)
B	-0.616 (-4.99)	-0.381 (-3.25)	-0.348 (-4.26)	-0.443 (-3.27)	-0.353 (-7.25)
C	-0.676 (-5.04)	-0.425 (-4.85)	-0.328 (-4.19)	-0.489 (-3.19)	-0.384 (-7.80)
D	-0.606 (-4.75)	-0.442 (-3.91)	-0.336 (-3.89)	-0.494 (-2.98)	-0.415 (-7.73)

Table 3.
Cross section estimates of convergence parameter β with models: A – D: 1995 – 2012

MODEL	Low income N = 90	Lower middle income N = 49	Upper middle income N = 55	High income N = 62	Total (median regression) N = 196
A	-0.263 (-10.54)	-0.154 (-8.83)	-0.057 (-2.73)	-0.147 (-7.73)	-0.069 (-10.92)
B	-0.355 (13.11)	-0.134 (-5.39)	-0.045 (-2.13)	-0.152 (-8.35)	-0.102 (-10.18)
C	-0.368 (-8.05)	-0.242 (-1.61)	-0.109 (-2.57)	-0.155 (-5.98)	-0.307 (-4.92)
D	-0.658 (-7.17)	-0.184 (-1.04)	-0.179 (-2.17)	-0.214 (-2.44)	-0.298 (-4.57)

Figure 4 depicts the quantile process β -coefficients (i.e. model estimation results at different error quantiles) of model A. The results indicate that it is the countries with largest absolute tuberculosis mortality growth rates (the lowest quantiles - typically the low-income countries, see Table 2: row A, Figure 3 and Appendix B) that have the largest β -convergence and countries with smallest absolute mortality growth rates have the smallest β -convergence. The observed OLS model residual heteroskedasticity and non-normality make the quantile estimation results to vary in different error quantiles (Davino, Furno & Vistocco, 2014). As OLS estimation is a method of regression mean in the sample it masks the different distribution features of data.

Figure 4.
Unconditional quantile process coefficients ($q = 0.1, 0.2, \dots, 0.9$) in 1970 – 2012 and 1995 – 2012 respectively with model A)

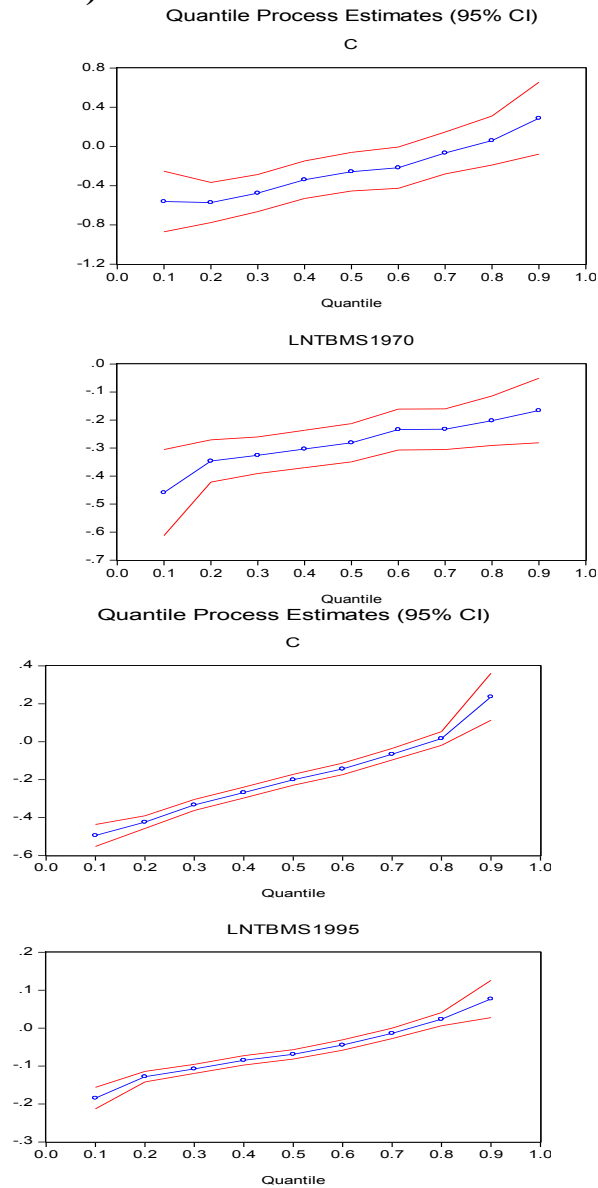


Figure 5
Unconditional quantile process coefficients ($q = 0.1, 0.2, \dots, 0.9$) in 1970–2012 and 1995–2012 respectively with model D

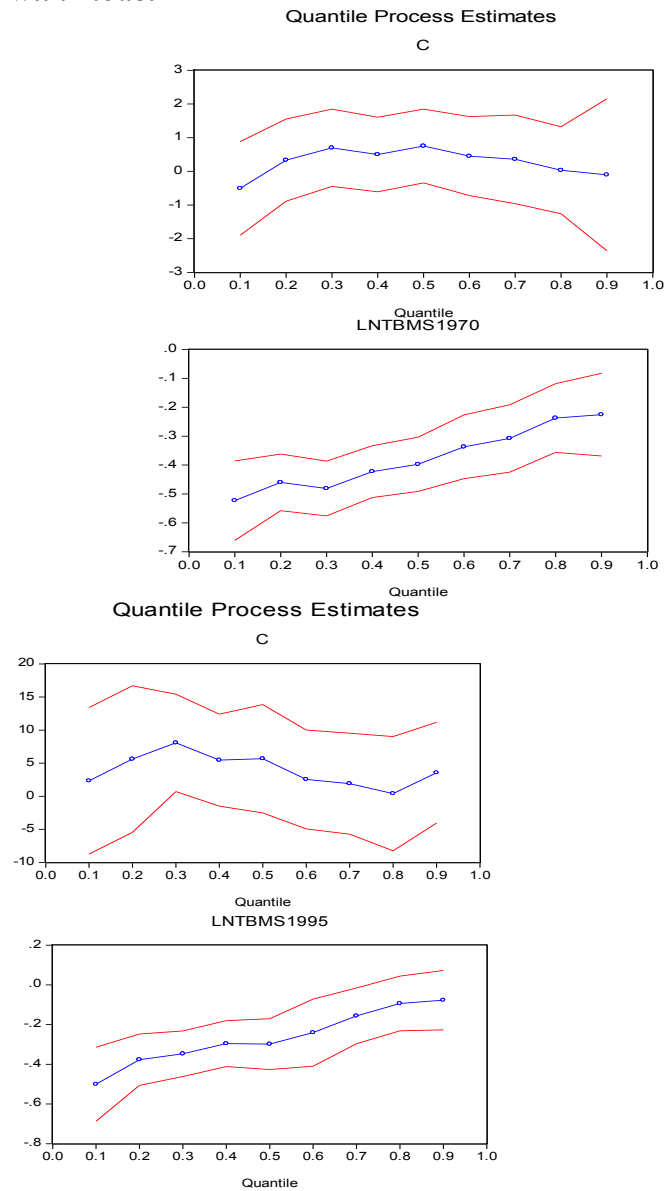


Figure 5. reports the quantile estimates with both control variable sets X_{i,t_0}^{TECH} and X_{i,t_0}^{SOC} . There are not big differences between the quantile process estimates between models A and D. Note that in growth empirics literature the constant term depicts the steady state growth rate. The quantile process estimates of constant term are mostly negative in model A) indicating that the negative growth rates in TB mortality are typical for countries with low level of mortality. For model D the constant term estimates are too imprecise to support this result.

Cancer mortality

Trend estimates. Tables 4 depicts the results of models:

$$\begin{aligned} A_1 : \quad & \ln y_{i,t} = a_{i,0} + b_1 T + \varepsilon_{i,t} \\ A_2 : \quad & \Delta \ln y_{i,t} = b_{i,1} + b_2^* T + \varepsilon_{i,t}^* \end{aligned}$$

We report results with 144 countries on periods 1970 – 2012 and 1995 – 2012 separately because in years 1970 – 1995 the cancer mortality rates in many countries were not measured with high precision. We observe that for low and lower middle-income countries the trend growth estimates are larger (in absolute terms) than for upper middle income and high-income countries in period 1970 - 2012. This is not found in period 1995-2012. However, the acceleration estimates (b_2 's) are negative only for high income countries only in the period 1970 – 2012 showing that cancer mortality is decreasing with increasing speed in these countries. Contrary to this one finds non-speeding-up in the other three groupings. A similar scenario is seen in the period 1995-2012.

Table 4
Trend model estimates of cancer mortality rates 1970 – 2012 and 1995-2012

MODEL	Low income N = 28	Lower middle income N = 27	Upper middle income N = 35	High income N = 54
$A_{1,1970-2012}:$ b_1	-0.013 (-63.99)	-0.011 (-78.72)	-0.008 (-48.71)	-0.005 (-37.75)
$A_{2,1970-2012}:$ b_2	0.0003 (7.68)	0.0003 (7.31)	0.0003 (6.25)	-0.0004 (-12.24)
$A_{1,1995-2012}:$ b_1	-0.007 (-18.39)	-0.005 (-11.84)	-0.003 (-8.93)	-0.009 (-66.39)
$A_{2,1995-2012}:$ b_2	0.00016 (1.17)	0.00025 (2.13)	0.0002 (1.48)	-0.00006 (1.89)

σ –convergence. Dispersion of cancer mortality rates for the high income countries are higher than the other income groups since 1970 (Figure 6). This is partly a result of higher average mortality rates in these countries (Figure 8). However when taking the low income countries as the starting point, one sees that there has been σ -convergence only in certain periods. Generally one does not see evidence of general or trending σ -convergence for non-high-income countries. Between 2000-2012 there is a weak σ -convergence in lower income and low income countries (Figure 7). However for the high income countries σ -convergence is evident only after year 1995 albeit the average cancer rates (Figure 8) are also declining for this income group in whole sample (Appendix B for group specific growth rates). The middle income and the lower income categories followed the same trajectory as the lower income group had. We stress the result that contrary to weak σ convergence the average cancer mortality rates declined during all the sample years. The high-income countries have still the higher-than-the-others average

cancer mortality rates. After 1995 the high-income level has started to decline faster and in other income groups average rates have halted.

Figure 6.
 σ – convergence 1970 – 2012

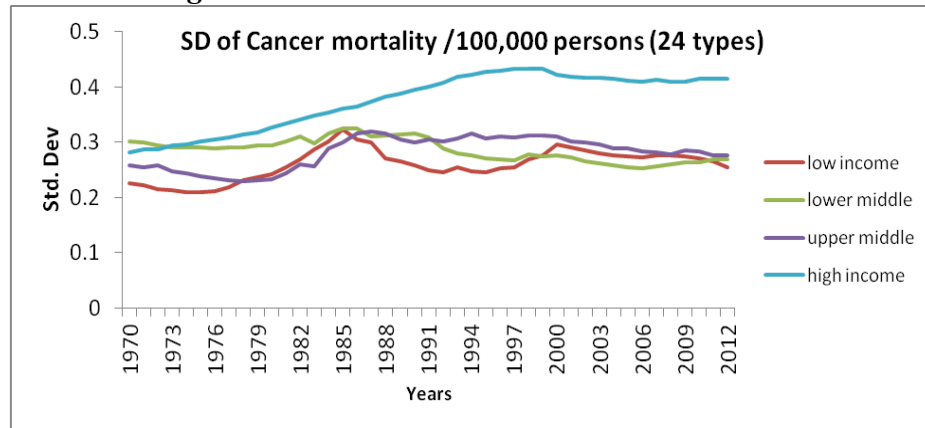


Figure 7.
 σ – convergence 1995 – 2012

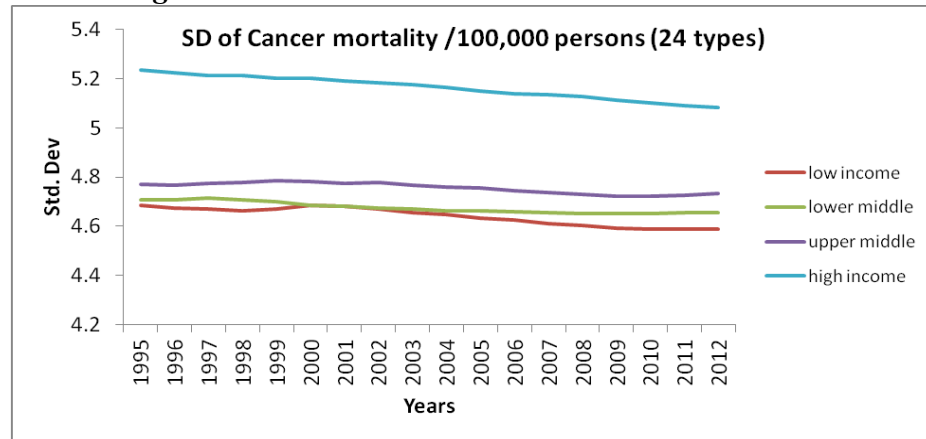
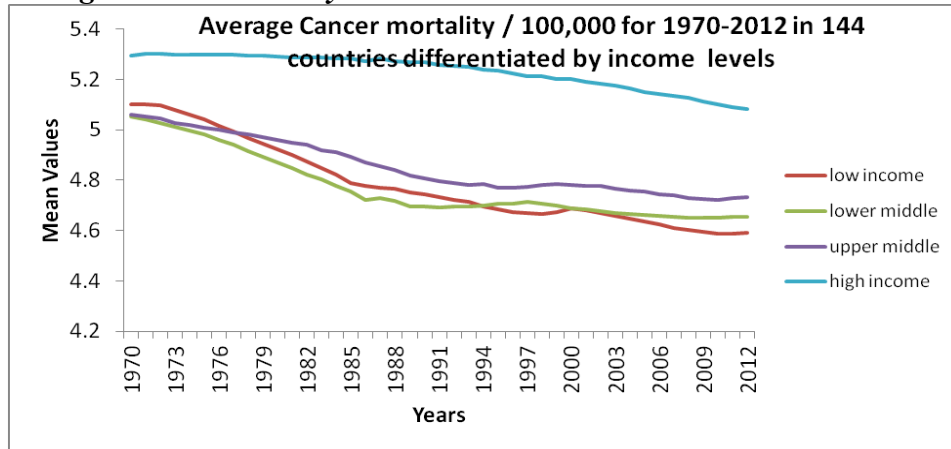


Figure 8.
Average Cancer mortality 1970 – 2012



β – convergence: cross section approach. In the cross-section approach, we take the same A – D models and use OLS and quantile methods to derive convergence estimates. In Table 5 the t -values show that almost all β coefficients are significant at 10% level. Both in case of median regression and high-income category for model A the estimate for β is non-significant. For upper lower middle-income countries adding socioeconomic variables have been an obstacle in the speeding up process of convergence. Low income countries have the best convergence situation in model D but some β estimates are unstable.

Table 5.
*Cross section estimates of convergence parameter β with
models A – D: 1970 – 2012*

MODEL	Low income N = 28	Lower middle income N = 27	Upper middle income N = 35	High income N = 54	Total (median regression) N = 144
A	-0.644 (-1.79)	-0.688 (-4.09)	-0.822 (-4.12)	0.137 (1.21)	0.065 (0.39)
B	-1.013 (-4.76)	-0.388 (-1.56)	-0.846 (-7.65)	-0.315 (-2.19)	-0.597 (-4.05)
C	-0.813 (-2.23)	-0.677 (-4.31)	-0.912 (-3.59)	-0.300 (-1.98)	-0.421 (-3.68)
D	-1.354 (-4.67)	-0.262 (-0.95)	-0.827 (-6.31)	-0.514 (-3.67)	-0.689 (-5.30)

In Table 6, with addition of more variables as one moves from models A to D, one sees that the speed of convergence increases (absolute value of β) when OLS for 144 countries for 1995-2012 is taken. However, this does not happen for low and lower middle-income countries with models C and D. Also for high-income countries models A and C show inconclusive results.

Table 6.
Cross section estimates of convergence parameter β with models A to D: 1995 – 2012

MODEL	Low income N = 28	Lower middle income N = 27	Upper middle income N = 35	High income N = 54	Total (median regression) N = 144
A	-0.352 (-9.05)	-0.473 (-13.19)	-0.253 (-10.54)	0.046 (2.97)	-0.058 (-5.55)
B	-0.479 (-18.12)	-0.441 (-11.43)	-0.379 (-17.87)	-0.076 (-4.21)	-0.246 (-17.79)
C	-0.181 (-1.15)	-0.055 (-0.57)	-0.299 (-3.08)	-0.134 (-1.59)	-0.201 (-3.81)
D	-0.281 (-1.16)	0.130 (1.33)	-0.496 (-3.89)	-0.159 (-1.97)	-0.237 (-3.97)

Quantile regression results (Figure 9) for model A in years 1970 – 2012 and 1995 – 2012 show only significant convergence for country growth rates in above 0.5 quantiles in years 1995-2012 - typical result for non-high-income countries (see Table 6: row A, Figure 8 and Appendix B). This does not strike against OLS results. However, the results with model D) show almost uniform β -convergence for all quintiles with significant 95% CI's.

Figure 9.
Unconditional quantile process coefficients ($q = 0.1, 0.2, \dots, 0.9$) in 1970 – 2012 and 1995 – 2012 respectively with model A)

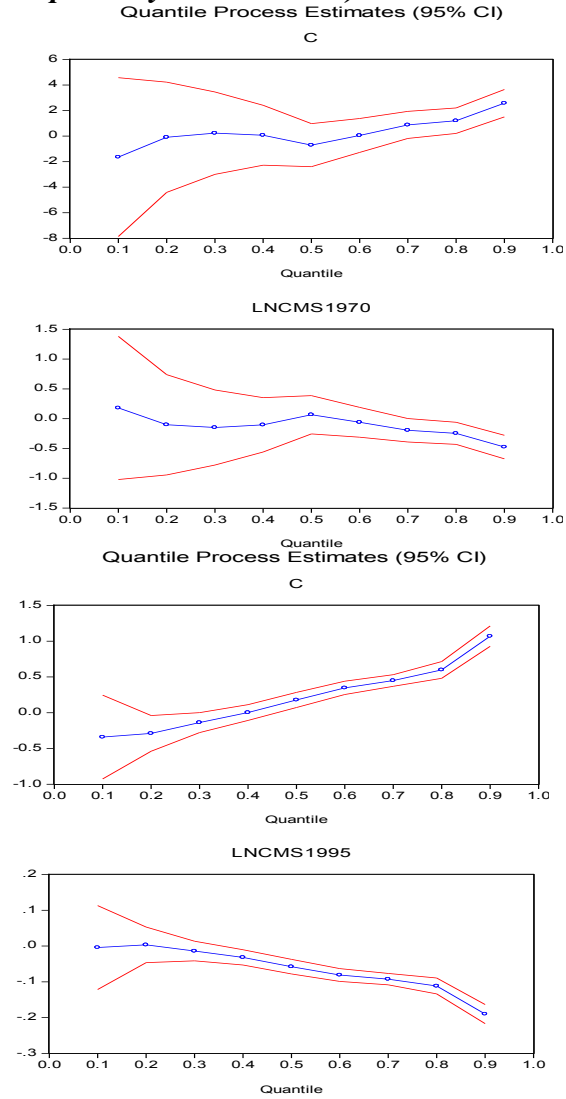
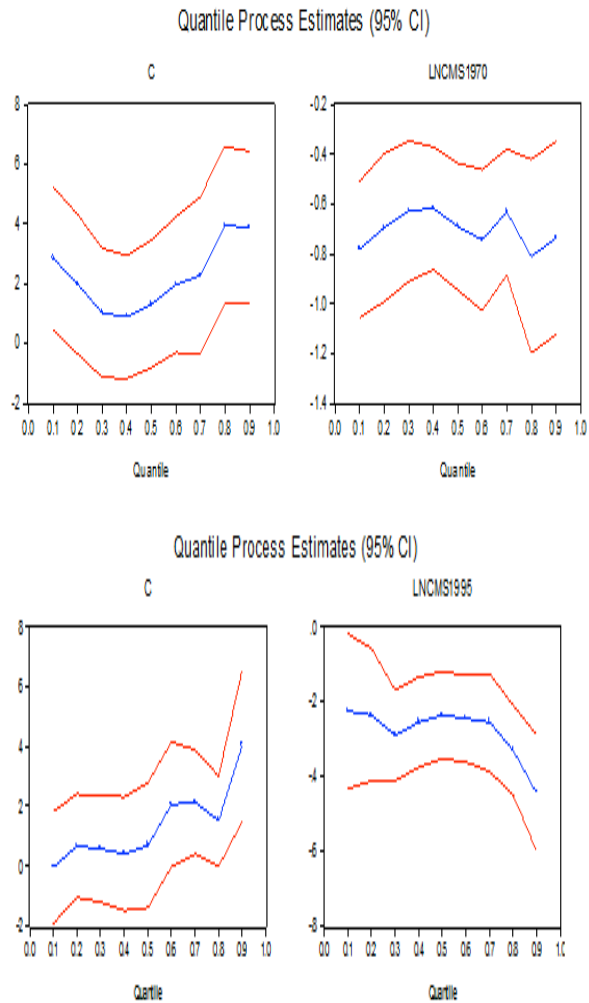


Figure 10.
Unconditional quantile process coefficients ($q = 0.1, 0.2, \dots, 0.9$) in 1970 – 2012 and 1995 – 2012 respectively with model D)



DISCUSSION AND CONCLUSIONS

For decreasing TB and cancer mortality rates the trend growth estimates are the largest in absolute terms in case of low income and lower middle-income countries. Whereas in TB mortality one sees a speeding up of declining mortality rate for not high-income countries, just the opposite effect is valid for cancer mortality rate, as the speed of decreasing cancer mortality rates is speeding up only in high-income countries.

Whereas one sees a σ -convergence trends in upper middle and lower middle-income countries till the early 1990s for TB mortality, in case of cancer mortality there is no such convergence. Overall, there is more evidence of σ -convergence in case of TB mortality than in case of cancer between 1970–2012. However, one can argue that average TB and cancer mortality rates are going down for all country groupings in 1970 – 2005 but in the period after it went up to 2012 the declining process has haltered especially for cancer in non-high-income countries.

Considering β -convergence (in terms of absolute values) for both cancer and TB, taking the cross-section growth between 1970–2012 in different income groups, one sees clear convergence with unconditional Barro-regressions for both TB and cancer mortality rates covering the period 1970 – 2012. For condition β -convergence, when health care technological and socioeconomic variables are taken into consideration, we find that for low income countries, the TB and cancer mortality rates respectively, have the fastest converge. However, when analyzing the period 1995-2012 having less erroneous measurements, TB in low-income countries still show the fastest β -convergence, but with cancer rates the convergence disappears when additional HCT and socioeconomic initial variables are added in test models. The

results with quantile regressions give additional insights to convergence analysis that are not obtained with fixed effects panel regressions. β - convergence is more evident across the quantiles in conditional models.

The results indicate that the cancer mortality rates are very country specific and when conditioning the rates in different income groups the convergence is not present anymore. The global (conditional) convergence still seems to be missing for cancer mortality rates albeit the average rates have declined almost to the current period. Contrary to cancer rate results the TB mortality rate results give implication that a catching-up of declining of TB mortality takes place in poorer countries through diffusion of HCTs from the richer nations. This phenomenon is however not yet clearly observed in cancer mortality rates where diffusion and disease processes are more heterogeneous than with TB.

One can argue that cancer mortality is not responding as well as TB mortality to diffusion of HCTs. Here one seems to forget the fact that prevalence, diagnosis and treatment of TB has been present for a while, while both the diagnosis and treatment of cancer effectively are comparatively a newer phenomenon. Existing therapies like chemo-, surgical-, radio, precision medicine, and (controversial) stem cell transplant, and many newer treatments for cancer (e.g., molecular targeted therapies) are in their pre-clinical test phases. Also, new or rare types of cancer are being diagnosed (e.g. chronic myeloid leukemia). This all happens in large scale only in the richer countries. Note also that R & D in new cancer treatments are more expensive than for new TB treatments like multi-drug resistant ones or that with HIV. Thus, it could take some time for new cancer treatments to diffuse to poorer countries.

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Appendix A

Data sources

The main TB data source has been WHO (2015b). TB mortality, TB incidence and prevalence data are available here. Individual country data has been collected in this database for many countries from their national databases. The main sources of OECD's cancer mortality and case statistics have been from International Agency for Research on Cancer (IARC, 2015a), IARC Cancer Mondial (IARC, 2015b), GLOBOCAN (2015) and OECD (2015a). Further data sources have been WHO (2015f) and IARC (2015c). Data for Nordic countries have been taken from NORDCAN (2015). Other data sources have been EUREG (2015), EUCAN (2015), CI5 (2015), OECD (2015c) and SURVCAN (2015). HCT (radiotherapy equipment, MRI units, CT scanners, mammography machines) data for both TB and cancer have been obtained from eclectic databases. The most important one for OECD data has been from OECD (2015b). Global (WHO, 2015c), including not OECD European countries (WHO, 2015d) as well as Europe's (Eurostat, 2015a) HCT data have been added to OECD data. BCG vaccination data (WHO, 2015e) has also been considered. This database includes WHO's global summary of vaccine preventable diseases monitoring system. This data has been further supplemented by UNICEF data (UNICEF, 2015a; WHO, 2015m). Health expenditure data has been acquired from WHO (2015k,

2015n), World Bank (2015f, 2015g & 2015h) and OECD (2015d). Global Health Expenditure Database of WHO (2015k) is one major data source here for all the countries, namely, OECD & other economies. The malnutrition variable relevant for TB - kilocalories per person per day is obtained from FAO (2015). Access to drinking water data has been obtained from World Bank (2015a) and United Nations (2015) databases. This is also one of the indicators that falls under United Nation's Milenium Development Goals. Population with access to proper sanitation data has been acquired from World Bank database (2015b, 2015c & 2015d). These variables are particularly relevant for the incidence, prevalence and prevention of TB. Data on hospital beds has been obtained from WHO (2015g) and World Bank (2015e) data sources. Alcohol consumption data (WHO, 2015g, 2015h; Quandl, 2015) and tobacco usage statistics (WHO, 2015g, 2015i & 2015j) have given a more holistic approach to the models since these variables act detrimentally against cancer and TB incidence, prevalence and cure.

However, data for TP_{kt} was available for 66 countries from 1970 to 2012. These countries cover the OECD countries, G20 countries, Western & Eastern European nations and former Soviet Republics. Data for San Marino and Macedonia were not available for the whole period. Hence, they are left out. Additionally, the data for the variables $THEXPC_{kt}$ and AW_{kt} were available for the period 1995 – 2012 for all the 196 countries. Hence these two variables are added for the said period when doing the regressions for 1995 – 2012. For the socioeconomic variable $THEXPC_{kt}$ data is available for all countries only from 1995 – 2012. Further, data for AW_{kt} , which is a socio-economic variable is available from 1990 onwards. Hence to keep parity with $THEXPC_{kt}$ variable, data from 1995 to 2012 has been taken for AW_{kt} .

Appendix B
Mean and Standard Deviation for TB and cancer growth
rates in 2012-1970 and in 2012-1995

Country groups	Mean	Std. Dev.	Obs.
1	-1.323292	1.025381	30
2	-1.268814	1.004639	49
3	-0.951953	0.865850	55
4	-0.881951	0.586311	62
All	-1.065862	0.868855	196

Figure 1. TB growth rates: 2012/1970

Country groups	Mean	Std. Dev.	Obs.
1	0.731410	0.793036	30
2	0.511728	0.708949	49
3	0.460702	0.684205	55
4	0.384494	0.387470	62
All	0.490787	0.637743	196

Figure 2. TB growth rates: 2012/1995

Country groups	Mean	Std. Dev.	Obs.
1	-0.512214	0.281326	28
2	-0.397330	0.325871	27
3	-0.327883	0.345064	35
4	-0.211975	0.265897	54
All	-0.333281	0.318391	144

Figure 3. Cancer growth rates: 2012/1970

Country groups	Mean	Std. Dev.	Obs.
1	0.096568	0.146128	28
2	0.053257	0.125605	27
3	0.037645	0.183233	35
4	0.151395	0.123652	54
All	0.094686	0.151279	144

Figure 4. Cancer growth rates: 2012/1995

Author's Biography

Devdatta Ray holds a Master of Social Sciences and Master of Arts and is a researcher in the Department of Health and Social Management at the University of Eastern Finland.