Relative mortality improvements across the developing world, 1990-2009

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Abstract: Using cross country regression analysis, this paper constructs a novel distance-to-frontier type metric for ranking countries by relative improvements in mortality. The method proposed in this paper connects to and extends a large demographic literature on "routes to low mortality" (Caldwell, 1986; Kuhn, 2010). The metric developed in this paper can also be used for tracking socio-economic inequality broadly defined (to include access of the poor to health infrastructure) over time for individual countries. Given the unavailability of reliable and consistent direct measures of inequality for most poor countries, especially related to non-income aspects of living standards, the metric developed in this paper can be used as an alternative indirect measure that is intuitive and easy to compute.

JEL Codes: I14, O57, I32.

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1. Introduction

In an extremely influential paper published in the *Population and Development Review* in 1986, John C. Caldwell developed a method for ranking countries according to relative improvements in mortality. The method entailed comparing country rankings by two criteria, per capita income and some health indicator (like infant mortality rate). If a country's rank according to the health indicator was 25 or more than its rank according to per capita income, then such a country was deemed to be a superior health achiever. Likewise, if a country's rank according to the health indicator was 25 or less than its rank according to per capita income, then such a country was deemed to be a poor health achiever. By drawing on cross country regression analysis, this paper proposes an extension of, and improvement over, Caldwell's (1986) method.

The extension proposed in this paper draws on a large body of literature which, starting with the pioneering work of Preston (1975), has studied the cross country relationship between income and

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health indicators (like infant mortality or life expectancy). Key features of the income-health relationship is depicted in Figure 1, which gives scatter plots of life expectancy at birth (LEB) against per capita income (measured at 2005 PPP $) for a group of 143 developing countries for four different years: 1990, 1995, 2000 and 2009. The scatter plots also include, for each of the four year, the estimated LEB from a bivariate regression of log-LEB on a constant and log per capita income.

[FIGURE 1 ABOUT HERE]

The main findings of this enormous, and growing, body of research on the income-health relationship, indicated in Figure 1, can be summarized as follows: (a) there is a strong, positive and stable relationship between LEB and per capita income (PCI) across countries; (b) the relationship is nonlinear and can be fruitfully captured by a log-log regression or a quartic regression; (c) the curve representing the relationship between LEB and PCI shifts over time (so that same PCI levels correspond to higher LEB over time); (d) the dispersal of LEB around the regression line declines with PCI; and (e) the statistically significant positive relationship between LEB and PCI holds even after controlling for other relevant factors like women's formal education, HIV-AIDS prevalence, etc., and seems to be very robust over time.[1]

The construction of relative rankings, in Caldwell (1986), as the difference in ranking according to the health indicator and per capita income was meant to capture both the fact that higher income can be expected, on average, to be associated with better health indicators, and that some countries can overcome constraints put on health achievement by income. This methodology for the construction of relative rankings can be improved by incorporating the five features of the income-health relationship that is listed above. Thus, we need to include additional controls, especially the prevalence of HIV-AIDS, allow for a time-improving and nonlinear relationship between income and health, and also allow the dispersal of countries across "average health performance" for a given level of per capita income to vary with per capita income itself. Since all these issues can be quite naturally addressed within a regression framework, as explained below, the method proposed in this paper is not only an extension of Caldwell (1986) but an improvement too.

The added advantage of the metric proposed in this paper is that it can be used to track changes in socio-economic inequality, broadly understood, over time. Since many developing countries lack reliable and consistent data on inequality, especially the non-income aspects of well-being, the metric proposed in this paper can be used as a first approximation to understanding changing patterns of inequality over time in a wide range of developing countries and regions.

Thus, this paper makes two important contributions. First, by connecting to and extending the method in Caldwell (1986), this paper offers a more robust relative ranking of countries with respect to mortality improvements over time. Second, it offers an intuitive and easy to compute metric that can be used to track changes in socio-economic inequality over time, thereby adding to the development literature on the empirics of inequality measurement.

[1] See Pritchett and Viarengo (2010) for a summary of this literature and interesting results spanning the period 1902-2007 for a very large cross section of countries.

The rest of the paper is organized as follows. Section 2 develops the standardized distance to frontier (SDTF) metric of relative mortality improvement. Section 3 introduces the data, presents regression results from cross country regressions, and provides a ranking of 69 developing countries in terms of relative improvements in mortality for the period 1990-2009. Section 4 introduces the discussion on the relationship of the SDTF and socio-economic inequality with some panel data regression results. In Section 5 trends in the SDTF metric are presented for some countries in South Asia, and sub Saharan Africa to illustrate our claim about the relationship between SDTF and socio-economic inequality. Section 6 presents some robustness checks and the following section concludes the paper with some thoughts about future research.

2. Distance to Frontier Metric and Socio-economic Inequality

2.1. Construction of the Metric

Let us call the regression curve (embedded in the scatter plots in Figure 1) the "medical technology frontier" and the regression residual for each country the "distance to frontier" (DTF) of that country (for the given year). The DTF for a country gives the amount, in years, by which the country exceeds (if the DTF is positive) or falls short of (if the DTF is negative) the average performance of countries in terms of LEB after controlling for per capita income and medical technological diffusion.[2] Thus, for every country and every year, the DTF provides a measure of *relative performance* in terms of LEB with respect to other countries with similar per capita income. An example of a scenario relating to the change in the distance to frontier (DTF) for some country between an initial and a final year is depicted in Figure 2. While the DTF metric is our starting point, we will need to make four refinements to this basic metric to arrive at our preferred measure of relative mortality improvements.

[FIGURE 2 ABOUT HERE]

First, we would like to control for the effect of HIV prevalence on LEB. The motivation for this is provided in Figure 3, which plots the LEB since 1960 for major regions of the world. All regions, other than sub Saharan Africa, have witnessed secular improvements in LEB over these past four decades. One of the major reasons behind the dismal performance of sub Saharan Africa is the HIV epidemic. Beginning in the early 1990s, the spread of HIV-AIDS has had a major negative impact on the health and living standards of the population in sub Saharan Africa; gradually it has spread elsewhere as well. Hence, it is important to control for the impact of HIV-AIDS on LEB.

[FIGURE 3 ABOUT HERE]

[2] What I have termed the medical technology frontier is very unlike a production possibilities frontier; no efficiency considerations underlie the medical technology frontier. It is, rather, the average performance given income and medical technology. Thus, the DTF should be understood as an abbreviation for "distance from average performance after controlling for per capita income and medical technology diffusion".

Second, we would like to take account of two-way causality. Since it is plausible to argue that the effect between income and health runs both ways, ordinary least squares estimates of the DTF (the regression residual) will provide us with biased and inconsistent measures. Hence, we need to find suitable instruments for log-per capita income and estimate the parameters with two stage least squares to arrive at consistent estimates of DTF.

Third, we need to take account of the fact that the variance of DTF (the regression residual) is itself a function of the level of per capita income. Thus, for instance in Figure 1, the dispersal of LEB across the regression curve is much higher at low levels of per capita income than it is at high levels of income. Thus, the same "distance" from the regression curve, which is captured by the DTF metric, has a different real import depending on the level of per capita income. To take account of this issue, we will "standardize" the DTF metric by dividing it with the standard deviation of the DTF in the decile to which a particular country belongs, and call it the standardized distance to frontier (SDTF).

Fourth, to remove the impact of short run fluctuations from the picture we will use a 5 year average of the SDTF at the initial and final years that we wish to compare. For instance, in this paper, we will be comparing the year 1990 and 2009. Hence, we will compute the average SDTF over the period 1990-94 and compare it to the average SDTF for the period 2005-09.

Fifth, and finally, we will define an "improvement metric" as the difference in the average value of the SDTF for the period 2005-09 and the average SDTF over the period 1990-94. We will use this improvement metric to rank relative improvements in mortality across countries.

Let us now concretize this discussion using some algebraic notations. To be more precise, we will start with the following augmented Preston regression:

(1) $$LLEB_{it} = \alpha_t + \beta_t \times LPCI_{it} + \gamma_t \times HIV_{it} + \varepsilon_{it},$$

where HIV denotes the prevalence rate of HIV in a country; with the augmented regression, the predicted value of *LLEB* for country *i* in year *t* given by

(2) $$\widehat{LLEB}_{it} = \hat{\alpha}_t + \hat{\beta}_t \times LPCI_{it} + \hat{\gamma}_t \times HIV_{it}.$$

For country *i* in year *t*, the distance to the frontier becomes

(3) $$DTF_{it} = LLEB_{it} - \widehat{LLEB}_{it} = \hat{\varepsilon}_{it},$$

where hat-quantities denote predicted values computed from the regression. To compute the standardized DTF, we divide DTF for country *i* in period *t* by the standard deviation of the DTF for the decile to which the country belongs, i.e.,

(4) $$SDTF_{it} = \frac{DTF_{it}}{\sigma_{jt}},$$

where σ_{jt} is the standard deviation of the regression errors (DTFs) for countries in the decile to which country *i* belongs with $j = 1,2, \dots, 9$.

Averaging the SDTF measure over five years around the initial time period *t* (where averaging is done for 5 periods going into the future) gives us

(5) $ASDTF_{it} = \frac{\sum_{j=0}^{4} SDTF_{it+j}}{5}$, and

Averaging around the final time period T (where averaging is done for 5 periods going back into the past) gives us

(6) $ASDTF_{iT} = \frac{\sum_{j=0}^{4} SDTF_{iT-j}}{5}$.

We can now use the difference between the average SDTF at the two end points of our period of interest to construct our measure of relative improvement. Denoting this (relative) improvement metric as *IM*, its value for any country *i* between periods *T* (final period) and *t* (initial period) can be written as:

(7) $IM_{T,t}^{i} = ASDTF_{iT} - ASDTF_{it}$.

This metric is an extension and improvement over the relative ranking metric that Caldwell (1986) used because it takes account of the nonlinear, time-improving relationship between income and health and allows us to factor out the impact of the HIV epidemic and the dependence of the dispersal of DTF on per capita income. Thus, the metric proposed in this paper controls for country-specific income growth, "exogenous" progress in medical technology that is potentially available to all countries to adopt, and HIV prevalence rates. We will use this metric to capture relative mortality improvements over time and rank performance of countries for the period 1990-2009.

While the magnitude of the improvement metric is useful to rank countries, it is also worthwhile distinguishing at least four interesting cases relating to the sign and value of the improvement metric.

Case 1 (negative switch): the country is above average in the initial year ($ASDTF_{it} > 0$) but its position worsens relative to the average and it ends up below average in the final year ($ASDTF_{iT} < 0$); the improvement metric will be unambiguously negative ($IM_{T,t}^{i} < 0$), providing evidence of relatively poor health achievement.

Case 2 (positive switch): the country is below average in the initial year ($ASDTF_{it} < 0$) but improves its position and ends up above average in the final year ($ASDTF_{iT} > 0$); the improvement metric will be unambiguously positive ($IM_{T,t}^{i} > 0$), providing evidence of relatively high health achievement.

Case 3 (negative persistence): the country is below average in the initial year ($ASDTF_{it} < 0$) and continues to remain so in the final year ($ASDTF_{iT} < 0$); there will be two sub-cases depending on the relative magnitudes of *DTF* in the initial and final years so that if the improvement metric might turn out to be positive even with negative persistence if $ASDTF_{it} < ASDTF_{iT} < 0$.

Case 4 (positive persistence): the country is above average in the initial year ($ASDTF_{it} > 0$) and continues to remain so in the final year ($ASDTF_{iT} > 0$); again, there might be two sub-cases depending on the relative magnitudes of *DTF* in the initial and final years but the improvement metric might come out negative even with positive persistence if $0 < ASDTF_{iT} < ASDTF_{it}$.

Cases 1 and 2 are of great interest to us, and in the empirical analysis I will indicate countries that fall into either category. Case 1 gives unambiguous evidence for a deterioration of LEB compared to other countries after income growth and technological progress has been accounted for; case 2 indicates the exact opposite: unambiguous evidence of relative improvement.

3. Main Results

3.1 Model and Data

To recap, the metric proposed in this paper will use an Augmented Preston regression

(8) $$LLEB_{it} = \alpha_t + \beta_t \times LPCI_{it} + \gamma_t \times HIV_{it} + \varepsilon_{it}$$

where *LLEB* denotes log-life expectancy at birth, *LPCI* denotes log-per capita income, *HIV* denotes the prevalence of HIV-AIDS among the 15-49 population, and ε is an error term. The augmented Preston regression (8) will be estimated for every year between 1990 and 2009. Estimates of the residual will be used to construct the SDTF measure and the improvement metric, *IM*, for every country in the sample. While the IM metric will be used to rank countries over the period 1990-2009, the trend in the SDTF metric over the same period will be used to throw light on the direction of changes in socio-economic inequality within some countries and across some regions of the world.

3.2 Data

The sample of countries that figure in the analysis in this paper are a group of 143 developing countries which are categorized as low income, low middle income or upper middle income countries by the World Bank. Data on life expectancy at birth (measured in years), PPP per capita GDP (measured in 2005 international dollars) has been extracted from the World Development Indicators (WDI) online data base for the years 1990-2009.[3]

Data on HIV prevalence (measured as estimated percentage of the population between 15 and 49 years of age living with HIV) is taken from the GAPMINDER online data base. The basic data is from UNAIDS but GAPMINDER provided estimates for some countries for years before 1990. Since the data before 1990 is sparse, we use HIV prevalence data only for the years since 1990.[4]

[TABLE 1 ABOUT HERE]

Table 1 provides summary statistics for the variables that are used in this paper for four representative years, 1990, 1995, 2000 and 2009. The two variables of main interest for the analysis in this paper are per capita income and life expectancy at birth. For any country, PPP per capita GDP (measured in 2005 international dollars) measures the average household's per capita income adjusting for price changes across countries (PPP) and over time (2005 dollars); hence, it gives us a measure to compare real per capita income across countries and over time. Life expectancy at birth is the number of

[3] The WDI data base can be accessed here: http://data.worldbank.org/data-catalog/world-development-indicators

[4] The GAPMINDER database can be accessed here: http://www.gapminder.org/

years a newly born child can expect to live on average if the age-sex specific mortality rates remain unchanged; it provides one of the most important measures of mortality of the population.

Table 1 shows that mean per capita income declined between 1990 and 1995; since then, it has increased continuously to reach 5442 in 2009. Thus, there was a noticeable acceleration in mean per capita income since the mid-1990s. Between 1990 and 1995, mean per capita income decreased by about 0.89 percent per annum; between 1995 and 2000, the corresponding increase was 2.49 percent per annum. Between 2000 and 2009, growth accelerated so that mean per capita GDP increased by about 2.86 percent per annum. The second variable of interest, life expectancy at birth, has steadily improved from 1990 onwards: mean LEB increased from 61.38 years in 1990 to 62.36 years in 1995 to 65.34 in 2009. Interestingly, while mean per capita income declined by 4.4 percent between 1990 and 1995, mean LEB increased by about 1 year; on the other hand, even though mean per capita income increased by 13 percent between 1995 and 2000, mean LEB increased by only a similar amount (i.e., about 1 year).

Mean HIV prevalence in the 15-49 years age increased from 1.02 in 1990 percent to 2.77 percent in 2000. In the next decade, it declined to 2.48 percent in 2009. There is a rather large variance in HIV prevalence, with high prevalence rates in sub Saharan countries: the maximum value of HIV prevalence was 25.10 percent in 1995 and remained close to that figure at 25.90 percent in 2009.

3.3 Cross Country Regression Results

Table 2 gives results for a cross country regression of log LEB on log per capita GDP and HIV prevalence rate, for 1990, 1995, 2000 and 2009 respectively. The magnitude of the income elasticity of LEB (the coefficient on per capita income), which is strongly statistically significant in all the years, declines from 0.125 in 1990 to 0.117 in 1995 to 0.107 in 2009. Thus, in 1990, every percentage point increase in per capita income would be associated with 0.13 percentage point increase in LEB; in 2009, every percentage point increase in per capita income was associated with only a 0.10 percentage point increase in LEB.

[TABLE 2 ABOUT HERE]

The magnitude of the intercept, again strongly significant, increases from 3.137 to 3.291 to 3.335 over the same period. The increase in the estimated value of the constant term captures the expansion of the medical technological frontier over time; the decline in the estimated income elasticity captures the fact that as more countries become rich, the marginal impact of another percentage point increase in per capita income has proportionately lower impact on LEB.

The coefficient on HIV prevalence increases from -0.015 in 1990 (and 1995) to -0.017 in 2009; it is strongly significant in 1995, 2000 and 2009, pointing towards the massive impact that the AIDs epidemic has had on mortality since 1995, especially in the sub-Saharan countries. The interpretation of the magnitude of the coefficient is that of a semi-elasticity: in 1995, every percentage point increase in

HIV prevalence across countries reduced LEB by 1.5 years; in 2009, the corresponding reduction was 1.7 years. In the next section, I will use these regression estimates to construct the SDTF measure for every country and year between 1990 and 2009, and use it to construct an improvement metric (IM) that will provide information about relative improvements in mortality over this period.

3.4. World Ranking of Relative Mortality Improvement, 1990-2009

Table 3 provides rankings of countries according to *IM* computed on the basis of the cross country regression, estimates for which are reported in Table 2, for the period 1990-2009. Higher rankings go with lower improvement scores, i.e., value of IM, and thus indicate worse performance. Table 4 provides the list of countries which witnessed either positive or negative switch between 1990 and 2009.

The most striking difference in the rankings in Table 3 with those reported by Caldwell (1986) is that most of the superior health achievers in Caldwell's list do not figure in the top of the list according to my rankings. Thus, Thailand, Kenya and Ghana, which were examples of superior health achievers in Caldwell (1986) emerge as three of the worst performers in Table 3. Costa Rica, China, India, Sri Lanka, and Tanzania, again examples of superior health achievers in Caldwell (1986), figure in the middle or bottom half of my list. Thus, none of the countries which were examples of superior health achievers in 1982 according to Caldwell's (1986) measure, figure towards the top of the ranking list in Table 3.

What could be the reason for this striking difference in rankings? My hypothesis is that the growth process that took hold in these, and many other, countries since the mid-1980s has been profoundly disequalizing. The benefits of growth have been highly concentrated; thus, there has been negligible "trickle down". This has led to erosion of the relative advantage that these superior health achiever countries had in 1982. Four countries stand out as examples of such a disequalizing growth process, whereby they have grown very rapidly since the 1990s but have not managed to translate that rapid economic growth into improvements in LEB: China, India, Kenya and Thailand. All these countries figure in the *second half* of the list of rankings of countries in Table 3; India is ranked 47, China 41, Kenya 67 and Thailand 69 among 69 countries for whom ranking could be computed.

It might be thought that the improvement metric is biased against countries that have registered high growth over the period 1990-2009. This is not the case for three reasons. First, the comparison is made, at each point in time, with countries that have similar per capita income; hence all countries with similar levels of per capita income are treated in the same way. Second, the income-LEB relationship takes into account the inherent nonlinearity involved in the income-health relationship. Thus, the improvement metric already accounts for the fact that marginal increases in LEB calls for higher income growth as LEB increases. Third, the improvement metric also accounts for the fact that the distance from the regression curve changes with the level of per capita income.

The fact that the metric is not biased against high growth countries can also be seen from the rankings themselves. Countries with relatively high growth which also have shown rapid improvement in socio-economic inequality as measured by IM are: Bhutan, Bangladesh, Mozambique, and South Africa. This is in stark contrast to high growth countries with worsening socio-economic inequality like China, India, Thailand, and Sri Lanka. On the other side, there are countries which had low growth in real per capita GDP and also witnessed worsening socio-economic inequality. Examples of such countries are Central African Republic, Kenya, and Zambia.

[TABLE 3 ABOUT HERE]

The case of India is especially worrisome because it also figures in the list of 12 countries, along with Thailand, Zambia, Kenya, Ghana, Mauritius, Bulgaria, Belarus, Uganda, Malaysia, Cote d'Ivoire, and Mongolia which have witnessed a negative switch between 1990 and 2009. The negative switch implies that these countries had a better than average performance in 1990, but a worse than average performance in 2009. Hence, these countries give indication of significant worsening of inequality (and access of the poor to public health infrastructure) over this period. Two countries which are surprising entries in the list of poor health achievers, as we have already pointed out, are Sri Lanka (at rank 46/69) and Costa Rica (at rank 38/69). Since these had figured in Caldwell's (1986) list of superior health achievers, they certainly call for deeper investigation.

It is interesting to note that countries in sub-Saharan Africa show very divergent performances. While Rwanda, Botswana, Namibia, Niger and Madagascar are among the best performers, Zambia, Kenya, Ghana, Chad, and Republic of Congo are among the worst. The reasons behind these divergent performances need to be carefully investigated.

[TABLE 4 ABOUT HERE]

4. Relative Mortality and Socio-economic Inequality

4.1. Tracking Socio-economic Inequality over time with ASDTF

One interesting aspect of the income-health relationship captured by the scatter plots in Figure 1 is the enormous variation of LEB with per capita income. Figure 4 presents box plots of LEB by quartiles of per capita income for the same four years: 1990, 1995, 2000 and 2009. It is obvious from Figure 4 that there is substantial variation of LEB across per capita income classes for each of the four years. This variation across per capita income quartiles highlights the fact that factors other than per capita income and development (and diffusion) of medical technology affect health outcomes across countries. Pritchett and Summers (1996) draw attention to the same phenomenon using data on infant mortality rates in 1990 across a group of developing countries: "The large spread of health outcomes within each income quartile illustrates the extent to which factors other than income and secular trends influence health status" (pp. 844, Pritchett and Summers, 1996).

Several non-income factors impacting on health status have been stressed in the literature: effective public provisioning (Dreze and Sen, 1991), incidence of poverty and public health expenditure (Anand and Ravallion, 1993), the status of women (Caldwell, 1986), literacy and formal education of women (Hill and King, 1995; Williamson and Boehmer, 1997), access to safe drinking water (Macfarlane et al., 2000), access to advanced sanitation facilities, and extent (and severity) of undernutrition in the population (Husain, 2002; Mahfuz, 2008). If by the term socio-economic inequality we understand a broad notion of inequality that not only includes income and wealth inequality, but also non-income factors like the status of women, the position of religious, ethnic and racial minorities, and most importantly access of the poor to important public goods like adequate nutrition, education and health care that go towards building the "capabilities" of people in the sense of Sen (2001), then each of the non-income factor that impact on the health status of a population can be thought of as an aspect of socio-economic inequality. This is because positive redistribution and more effective public policy would improve average levels of each of these non-income factors.

Let us take adult literacy as an example. It is certainly the case that the bulk of illiterate people in a developing country will be the poor. Hence, when average literacy rates of the adult population increase, it is almost always the case that this is because of increase in literacy among the relatively poor; the rich are more or less already literate and hence there is not much scope for increase in literacy among the rich. Hence an increase in average literacy rates is also, and at the same time, a narrowing down of the gap in the literacy among the rich and the poor. Thus, when the average literacy rate in a poor country increases due to increase in primary education facilities, this leads to a decrease in socio-economic inequality. Hence, average levels of literacy, especially among women, can be seen as an aspect of socio-economic inequality. A similar argument can be advanced for effective public provisioning, access to safe drinking water, access to proper sanitation facilities, extent of under-nutrition, incidence of poverty, income distribution and other such non-income factors.

Thus, on the one hand there is a large literature that provides evidence of the impact of non-income factors, *most* of which can be construed as aspects of socio-economic disparity, on health status; on the other hand, Figure 4, and a similar figure in Pritchett and Summers (1996), shows that LEB varies substantially across per capita GDP quartiles. This suggests that information about the variation of LEB across income classes can be used for tracking changes in the direction of socio-economic inequality within countries over time.

Another way to appreciate the importance of these non-income factors and their relationships to socio-economic inequality is to recognize that improvements in LEB (and possibly other indicators of living standard as well) over time for any country can be decomposed into three broad parts. The first part arises due to increases in per capita income, and is highlighted by the positive slope of the regression curve in the scatter plots in Figure 1.

The second part comes from improvements in, and diffusion of, medical technology, and is highlighted by the upward "drift" of the regression curve (in the scatter plots in Figure 1) through time.[5] This upward movement of the regression curve is akin to the expanding technology frontier through time and is driven by improvements in, and diffusion of, medical technology that reduce the impact of diseases on the general health of human populations. Improvements in pre and post natal care, access

[5] In a cross country regression model, medical technology factors would be captured by the constant term; in a panel data regression model, the same set of factors would be captured by time fixed effects.

to hospitals (or medical professionals) for childbirth, and availability of generic drugs for dealing with common diseases like diarrhea, malaria, TB and AIDS can have an enormous positive impact on LEB; it is the beneficial impacts of medical technological change that is captured by the upward movement of the regression curve.

The third part can be attributed to the whole complex sets of factors (institutions of governance, public policy stance, effectiveness of public provisioning, status of disadvantaged groups like women and other minorities, etc.) that *distribute* income growth and access to medical technology across various sections of society. Once income growth and improvements in medical technology (and other relevant exogenous factors) have been controlled for, improvements in LEB would be positively impacted by redistribution (broadly defined to include access to public goods like education, and health care) towards the poor; redistribution away from the poor, i.e. increase in societal inequality, would have negative impacts on improvements in living standards. The regression residual in the scatter plots in Figure 1 normalized by the standard deviation of the DTF for the relevant decile, which I have called the SDTF, captures precisely this distributional aspect of the cross-country variation of LEB, which is the combined result of income and wealth distribution, effectiveness of public provisioning, and status of women (and other minorities) in society.

It is almost certainly true that the SDTF metric for any country for any given year will be impacted by a host of unobservable country specific factors, as also stochastic factors (random shocks); being contaminated by sundry country specific (like culture, governance, etc.) and stochastic factors (like weather events, for instance), the value of SDTF might not, in any given year, provide a very accurate measure of socio-economic inequality. But *trends in SDTF* (or *changes in the SDTF over periods of time*) for any country can provide us with information about the *direction of change* in socio-economic inequality in that country. This is because the country specific unobservable factors (like culture, governance) are likely to change only slowly over time; hence, their effect will be purged out when we track *changes* in the SDTF over time (or focus on the trend in the time series of SDTF for any country).[6] Thus, changes in SDTF for any country over time can provide a relatively accurate picture of changes in socio-economic inequality over time for that country. Hence, changes in SDTF (the standardized regression residual from a cross country regression like that depicted in Figure 1) can be used as an *indirect measure of changes in aggregate socio-economic inequality*, understood in a broad manner, over time for any country.

Since the SDTF captures the effect of all non-income factors that impact on health outcomes, changes in SDTF will necessarily be only a crude measure of changes in socio-economic inequality. While it seems plausible that most of the non-income factors will work in the same direction, it cannot be ruled out that there might also be cases where non-income factors work against each other. But even this crude and indirect measure is useful as a marker of the direction of change in socio-economic

[6] The effects of random shocks can be removed by averaging across time for every country. The time series plots of SDTF, in Figures 4, 5, 6 and 7 below, do not provide evidence of the presence of significant random country-level shocks. Hence, we do not take recourse to time averaging other than for the construction of the "improvement metric" (IM).

inequality. There are at least three reasons that make this indirect measure attractive to researchers and policy makers.

First, there is a big problem of unavailability of income distribution data for much of the developing world. For instance, between 1990 and 2009, income distribution data was available in the World Development Indicators between a maximum of 25 per cent of countries in 2000, and a minimum of 6 percent of the countries in 1990. Thus, even in the best case scenario, about 75 percent of developing countries do have income distribution data available.

Second, when data on income or consumption expenditure distribution is available for developing countries its quality is often low and they are beset with well-known problems. Changes in definitions or survey methodology often make comparability over time difficult.[7] It is also well understood that household surveys suffer from the problems of under-reporting and under-coverage of the richer sections of the population (Banerjee and Piketty, 2005). Even when reliable data on income distribution is obtained, it is not easy to convert that to measures of aggregate inequality like the Gini coefficient.

Third, traditional measures of income inequality capture only a narrow slice of socio-economic inequality because, by construction, they leave out non-income dimensions of socio-economic inequality like mortality, incidence and burden of common diseases, nutrition, educational attainment and social status deriving from factors like caste, race or ethnicity. While it is difficult to capture *all* non-income aspects of inequality in one simple measure, LEB has been proposed as a broad social indicator of social well-being that captures many of the important dimensions of living standards that are left out by pure income measures (Pandey and Nathwani, 1997). Ideally, one would like to track improvements in LEB across income classes to get an idea of the evolution of broad socio-economic inequality. Pandey and Nathwani (1997) use LEB data across broad income classes to construct a direct measure of socio-economic inequality; they demonstrate the use of their methodology using Canadian data. But data on LEB disaggregated by income classes is typically not available for most countries, especially poor countries. Hence, one needs to fall back on an indirect method to track changes in broad socio-economic inequality over time in poor countries. The method proposed in this paper develops one such indirect measure. Its main strengths are that it is fairly intuitive and easy to compute.[8]

The indirect measure proposed in this paper also highlights the important but oft-neglected point that as much as, or more than, economic growth itself the nature of that growth matters. High growth which is accompanied by worsening inequality (and reduced access of the poor to public goods) reduces the positive impact of income growth on living standards, especially of the poor. Conversely,

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[7] For an introduction to these data issues in the context of India, see Deaton and Kozel (2005).

[8] There is a large body of literature that studies the impact of income inequality on health outcomes in advanced capitalist countries; for a review of this literature, see Wilkinson and Pickett (2006). This paper shares the concerns of that literature but probably comes at the issue from the opposite end. While the literature reviewed by Wilkinson and Pickett (2006) finds strong evidence of the negative impact of inequality on health when comparison areas are geographically large, this paper argues that improvements (or deterioration) of LEB over and above that accounted for by income growth (and other relevant covariates) can be a proxy of socio-economic inequality.

even low economic growth that is more equitably distributed can have a significantly large impact on the material conditions of the poor.

Note that the distribution of the metric across countries can provide useful knowledge about the disparity in improvement across countries and regions, which can be useful for monitoring differential progress across regions; the latter can, in turn, be fed into policy formulation and implementation targeting laggard regions.

4.2 Results from Panel Regressions

In this section, I present some preliminary results in favour of the claim that changes in the SDTF over time can be understood as a marker of broad socio-economic inequality, which includes, other than income inequality also effectiveness of public policy, public provisioning of health care and education, and the status of women, and other such indicators.

[TABLE 5]

To test the relationship of the SDTF metric to broad measures of socio-economic inequality, I run separate bivariate regressions using a panel data set with data on the SDTF metric, the ratio of the income of the top to the bottom quintile, and per capita public health expenditure. Income distribution is meant to capture the income aspect, and per capita public health expenditure is meant to capture the non-income aspects, of socio-economic inequality. I also report results from a multivariate regression with both variables included in a single specification. The model I estimate is

(9) $$SDTF_{i,t} = \alpha_i + \beta * X_{i,t} + \varepsilon_{i,t},$$

where SDTF denotes the SDTF metric, X stands, in turn, for income distribution, and per capita public heath expenditure, α stands for a country-specific fixed effect, *i* indexes countries and *t* indexes years. Table 5 presents results of estimating β in (9) using a fixed effect (FE) estimation procedure.

Both income distribution and per capita public health expenditure have the expected signs in the bivariate and multivariate regressions. Columns (1) and (2) have estimates of the coefficient on income distribution and per capita public health expenditure in separate bivariate regression. The positive coefficient estimate on income distribution – the ratio of the income share of the top to the bottom quintile – indicates that higher income inequality is associated with a higher value of the SDTF metric, exactly as we would expect. The magnitude of the estimate suggests that each percentage point increase in the income share of the top quintile (relative to the bottom) leads to an increase in the SDTF metric by 0.12. The sign of the coefficient on per capita public health expenditure is negative, suggesting that higher public health expenditures are associated with lower values of the SDTF metric. Every percentage point increase in per capita public health expenditure is associated with a fall in the DTF metric by about 1.06 standardized years. Thus, the impact of per capita public health expenditure seems to be an order of magnitude higher than measured income inequality.

The results reported in column (3) in Table 5 refer to the multivariate regression. Both income inequality and per capita public health expenditure retain their original signs, but the statistical significance of income inequality is lost. Public health expenditure remains statistically highly significant with the coefficient estimate suggesting a very large impact of increases in per capita public health expenditure. The loss of statistical significance for income inequality might be due to mismeasurement in the income share ratio: it is well known that top income shares are severely underestimated in sample surveys, which might bias the measure of income inequality and lead to incorrect or weak results.

5. Divergent Country Performances, 1990-2009

We would now like to connect up the time series evolution of the SDTF metric and changes in socio-economic inequality for a set of countries. Figures 5 and 6 plot the SDTF for selected groups of countries in South Asia, and sub Saharan Africa. The most striking feature of the time series plots of SDTF is the visible lack of random fluctuations in the year to year movement of SDTF for each country; hence, the effect of random shocks in driving the movement of SDTF over time seems to be rather attenuated, if at all present. In fact, the SDTF metric for each country displays a smooth movement and strong persistence over time.

Divergent performance of countries in the same region, as depicted in Figure 5 and 6, on the other hand reinforce the case for using changes in SDTF as a relatively accurate marker of changes in socio-economic inequality. This is because countries in the same region can be plausibly expected to share both many unobservable factors and random shocks. Since the SDTF metric has already controlled for per capita income and medical technological change, and since random shocks seem unimportant, divergent movements of the SDTF among countries in the same region must be driven by the whole host of non-income factors that impact on socio-economic inequality. Looking at a set of South Asian and Sub-Saharan countries can illustrate this point.

5.1. South Asia

Figure 5 plots the DTF metric over the period 1990-2009 for the main South Asian countries: Bangladesh, India, Nepal, Pakistan and Sri Lanka. There is a striking difference in the evolution of the metric for these South Asian countries. While Nepal and Bangladesh give strong evidence of improvement in socio-economic inequality and access of the poor to basic public goods, Pakistan shows stagnation and Sri Lanka shows worsening over this period though it remains an above-average performer. Bhutan has been a below-average performer all through the period, though its distance from average performance has been declining over time; that indicates some improvement over time.

The big exception is India which shows not only a steady worsening of socio-economic inequality but a switch from an above to a below average performer country. A more detailed historical and institutional analysis of each of these South Asian countries needs to be taken up to understand the reasons behind this divergence. While such an analysis will be taken up in future research, it seems safe to conclude from this evidence in Figure 5 that the effects of rapid economic growth since the 1990s has not percolated down to the poorer sections of Indian society. In fact, it seems to have worsened socio-economic inequality and curtailed access of the poor to essential public goods like health care and education.

The fact that India, despite its high economic growth, has not been doing particularly well on the social well-being front has been noted by development economists like Jean Dreze (2004) and Amartya Sen (2011). Both have, in fact, compared India's dismal performance on various measures of living standards with the much better performance of Bangladesh. The fact that the DTF metric moves, between 1990 and 2009, secularly down for India, and moves almost secularly up for Bangladesh (and Nepal), is in line with the already-noted divergence between India and Bangladesh. This suggests that the crude and indirect measure proposed in this paper might, at least as a first approximation, provide reliable information about the direction of change in socio-economic inequality in other countries too.

5.2. Sub-Saharan Africa

Figure 6 plots the DTF metric for the period 1990-2009 for some sub-Saharan countries. Countries in sub-Saharan Africa have generally performed much worse than average other than a few notable exceptions like Botswana, and Eritrea. Nigeria and Angola have remained very far below average throughout this period. Among the countries which have witnessed significant deterioration in socio-economic inequality since 1990 are Kenya, Ghana and the Republic of Congo. Kenya and Ghana were above average performers in the early 1990s; by the late 2000s, both had switched their relative position to become below average performing countries. Congo was close to average in the early 1990s but rapidly lost ground since then.

6. Robustness Checks

The SDTF metric that has been computed in this paper so far relates to life expectancy at birth. It captures the "distance" from the average performance of developing countries given its per capita income level and the diffusion of medical technology potentially available to all countries. I have argued that the changes in the SDTF metric can be used as a measure of the direction of change in socio-economic inequality. Is the SDTF metric robust to the indicator of living standard?

To evaluate the robustness of the SDTF metric, I have computed a similar metric for two other commonly used indicators of living standard: infant mortality rate (IMR) and under-5 mortality rate (U5MR). The SDTF metric for IMR (U5MR) is derived from a bivariate regression of IMR (U5MR) on per capita GDP and a constant, and is defined as the predicted value *less* the actual observed value. Hence a positive value of the SDTF metric with respect to IMR (U5MR), say, for any year implies a lower value of the IMR (U5MR) than the average for the developing countries at the same level of per capita income; this suggests above average performance. Similarly a negative value of the SDTF metric implies below average performance.

Figure 7 plots the SDTF metric for both IMR and U5MR for two sets of countries: (a) those that have shown large improvements in socio-economic inequality between 1990 and 2009 (and have figured on the top of the list in Table 3), and (b) those that have shown large deterioration of socio-economic inequality in the 1990-2009 period (and have figured at the bottom of the list in Table 3). The countries in the first group are: Namibia, Nepal, Mozambique, Guatemala, Peru, Bangladesh, and Brazil; the countries in the second group: India, China, Ghana, Kenya, Thailand, Republic of Congo, Chad and Sri Lanka.

The charts on the right column in Figure 7 show that, in general, the countries that displayed large improvements in socio-economic inequality with respect to the SDTF metric on LEB, i.e., countries in the first group, have also performed well with respect to the SDTF metric on IMR and U5MR. This is because the SDTF metric with respect to both IMR and U5MR (charts on the right column in Figure 7) increase over time between 1990 and 2009.

Similarly, the charts on the left column in Figure 7 show that, again in general, the countries that displayed large deterioration in socio-economic inequality with respect to the SDTF metric on LEB, i.e., countries in the second group, have also performed worse with respect to the SDTF metric on IMR and U5MR. This can be seen from the charts in the left column of Figure 7, where the SDTF metric either declines over time, or remains flat. No country in this group shows an increase in the SDTF metric over time. Hence, the SDTF metric with respect to both IMR and U5MR show expected time series movements. Thus, the SDTF metric seems to be robust across many important indicators of living standard.

6. Conclusion

This paper has developed an extension of the measure of relative improvements in mortality proposed in the influential analysis of Caldwell (1986). The extension uses a cross country regression framework and can, therefore, take account of the non-linear and time-improving health-income relationship. It also allows for the effect of the HIV epidemic and for the fact that lower per capita income levels display larger variation in LEB across the regression curve. The measure developed in this paper is what I have termed a standardized distance to frontier (SDTF) type metric. The value of the SDTF for a particular country is the residual for that country from a cross country regression of log LEB on log per capita GDP, HIV prevalence rate and a constant, normalized by the variance of the residuals for the income decile to which the country belongs. It measures the performance of a country *relative to average performance* across the reference group of countries (countries in the developing world, say) after taking account of income growth, diffusion of medical technology, and HIV prevalence rates. Hence, it is an intuitive and rigorous measure to rank relative performance of countries on mortality improvement.

Ranking countries using the improvement in the SDTF over the period 1990-2009 gives results which are strikingly different from the rankings offered in Caldwell (1986). All the superior health achievers in Caldwell (1986) emerge, in my ranking list, as inferior health achievers. The reason for this dramatic reversal in rankings is the nature of the growth process underway in many of the erstwhile superior health achievers. My hypothesis is that the growth process has been extremely disequalizing so that the benefits of growth has been concentrated at the top of the income and wealth distribution. Hence, rapid economic growth has not translated into similarly large improvements in health indicators.

This intuition has led me to argue that the metric for relative improvements in life expectancy at birth (LEB) across countries that has been proposed in this paper can also be used as an indirect measure of socio-economic inequality (broadly defined to include access of the poor to essential public goods like education and health care). The residual in a cross country regression of log LEB on log per capita GDP, HIV prevalence rate and a constant measures the performance of a country *relative to average performance* across the reference group of countries (countries in the developing world, say) after taking account of income growth, diffusion of medical technology, and HIV prevalence rates. I have argued that changes in this residual can be used as an indirect measure of the direction of changes in broad socio-economic inequality for low and middle income countries.

Given the relative lack of reliable data on income and wealth distribution for developing countries, and the complete lack on data on the distribution of non-income dimensions of inequality, the indirect measure proposed in this paper can be utilized by researchers and policy makers to get a first approximation of the direction of change of socio-economic inequality across countries. The measure is intuitive and easy to compute.

I have illustrated the use of this metric by ranking countries for the period 1990-2009 and also by plotting the SDTF for a range of countries across South Asia, and sub Saharan Africa. Countries which have witnessed worsening inequality, with or without economic growth, have also performed poorly when ranked by the standardized distance to frontier (SDTF) metric; notable examples of countries which witnessed rapid economic growth but worsening socio-economic inequality are India, Kenya and Thailand.

There are several issues emerging from this study that requires further analysis. First, individual country and regional experiences need careful study that pays close attention to historical and institutional factors. In this paper, I have highlighted the stark divergent trends observed, for instance, in South Asia. Understanding these divergent experiences in a comparative framework needs to be taken up in the future. Second, the robustness of the SDTF metric needs to be evaluated. It is possible that the metric is more useful for the study of low and middle income, in comparison to high income, countries. If that is indeed the case, the reasons behind that needs to be understood, and a more comprehensive measure developed, if possible.

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Table 1: Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
1990					
PER CAPITA GDP (2005 INTL $)	122	3903.59	3261.15	400.06	14986.85
LIFE EXPECTANCY AT BIRTH (YEARS)	140	61.38	9.35	32.68	75.74
HIV PREVALENCE RATE (% of 15-49)	106	1.02	2.17	0.06	12.70
1995					
PER CAPITA GDP (2005 INTL $)	129	3731.95	3226.14	150.81	14899.05
LIFE EXPECTANCY AT BIRTH (YEARS)	142	62.36	9.49	29.10	76.80
HIV PREVALENCE RATE (% of 15-49)	106	2.22	4.18	0.06	25.10
2000					
PER CAPITA GDP (2005 INTL $)	133	4221.24	3578.75	254.06	18242.54
LIFE EXPECTANCY AT BIRTH (YEARS)	143	63.37	9.64	41.83	77.78
HIV PREVALENCE RATE (% of 15-49)	106	2.77	5.44	0.06	26.00
2009					
PER CAPITA GDP (2005 INTL $)	133	5441.87	4399.90	290.19	19308.25
LIFE EXPECTANCY AT BIRTH (YEARS)	136	65.34	9.43	44.30	79.04
HIV PREVALENCE RATE (% of 15-49)	107	2.48	5.00	0.06	25.90

Table 2: Regression Results

	DEP VAR: LOG LIFE EXPECTANCY AT BIRTH			
	1990	1995	2000	2009
PER CAPITA GDP (2005 INTL $)	0.125***	0.117***	0.112***	0.107***
	(7.00)	(7.01)	(10.09)	(10.65)
HIV PREVALENCE (% of 15-49)	-0.015**	-0.015**	-0.017***	-0.017***
	(-2.76)	(-4.48)	(-10.02)	(-11.34)
CONSTANT	3.137***	3.233***	3.291***	3.335***
	(21.71)	(24.2)	(36.89)	(39.67)
N	67	69	68	70
Instruments for per capita GDP	AGSH, GFCF	AGSH, GFCF	AGSH, GFCF	AGSH
OVERIDENTIFICATION ($\chi^2(1)$)	4.174	2.602	3.876	--
F-Stat (First Stage)	39.29	74.95	100.05	50.52

Note. 1. t statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001.

Note. 2. AGSH: share of agriculture in aggregate value added;

Note. 3. GFCF: share of investment in gross domestic product.

Table 3: Rankings of Countries by Relative Mortality Improvement, 1990-2009

Rank	Country	IM	Rank	Country	IM
1	Namibia	13.47	35	Mexico	-0.89
2	Nepal	12.46	36	Kyrgyz Republic	-1.02
3	Madagascar	8.32	37	Mongolia	-1.21
4	Rwanda	7.45	38	Costa Rica	-1.25
5	Tajikistan	7.43	39	Honduras	-1.51
6	Mozambique	7.23	40	Cote d'Ivoire	-1.94
7	Guatemala	7.21	41	China	-2.39
8	Nicaragua	7.01	42	Sudan	-2.52
9	Papua New Guinea	6.52	43	Chile	-2.76
10	Guinea	5.77	44	Georgia	-2.95
11	Ecuador	5.04	45	El Salvador	-2.98
12	Comoros	4.81	46	Sri Lanka	-2.99
13	Peru	4.24	47	India	-3.43
14	Indonesia	3.94	48	Malaysia	-3.65
15	Bangladesh	2.63	49	Russian Federation	-3.70
16	Gabon	2.43	50	Uzbekistan	-3.86
17	Turkey	2.40	51	Central African Republic	-3.91
18	Benin	1.81	52	Senegal	-3.96
19	Philippines	1.80	53	Paraguay	-4.97
20	Bolivia	1.57	54	Panama	-4.98
21	Botswana	1.40	55	Uganda	-5.12
22	Pakistan	1.24	56	Dominican Republic	-5.27
23	Egypt, Arab Rep.	1.19	57	Mauritania	-5.95

24	Swaziland	1.09	58	Belarus	-5.96
25	South Africa	1.04	59	Bulgaria	-6.26
26	Colombia	0.78	60	Mauritius	-6.61
27	Morocco	0.71	61	Congo, Rep.	-6.67
28	Latvia	0.56	62	Ukraine	-6.75
29	Algeria	0.34	63	Ghana	-7.59
30	Sierra Leone	0.28	64	Tunisia	-7.60
31	Tanzania	0.24	65	Romania	-8.07
32	Brazil	0.12	66	Lebanon	-8.62
33	Armenia	-0.11	67	Kenya	-10.46
34	Moldova	-0.70	68	Zambia	-15.51
			69	Thailand	-26.45

IM (improvement metric) = ASDTF(2009) – ASDTF(1990); for definitions of ASDTF see (5) and (6).

Table 4: Negative and Positive Switch, 1990-2009

Negative Switch		Positive Switch	
Country	**IM**	**Country**	**IM**
Thailand	-26.45	Madagascar	8.32
Zambia	-15.51	Mozambique	7.23
Kenya	-10.46	Guatemala	7.21
Ghana	-7.59	Guinea	5.77
Mauritius	-6.61	Benin	1.81
Bulgaria	-6.26	Egypt, Arab Rep.	1.19
Belarus	-5.96		
Uganda	-5.12		
Malaysia	-3.65		
India	-3.43		
Cote d'Ivoire	-1.94		
Mongolia	-1.21		

IM: improvement metric as defined in (7).

Table 5: IV Regression Results

	(1)	(2)	(3)
INCOME SHARE OF TOP TO BOTTOM QUINTILE	0.119***		0.102
	(3.76)		(1.58)
LOG PER CAPITA PUBLIC HEALTH EXPENDITURE		-1.063***	-1.549**
		(-4.03)	(-2.62)
CONSTANT	-0.207	9.965***	14.21*
	(-0.48)	(4.23)	(2.57)
N	348	1045	286
R-sq	0.048	0.016	0.040

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001
Note. See (9) in the text for details of the regression specification.

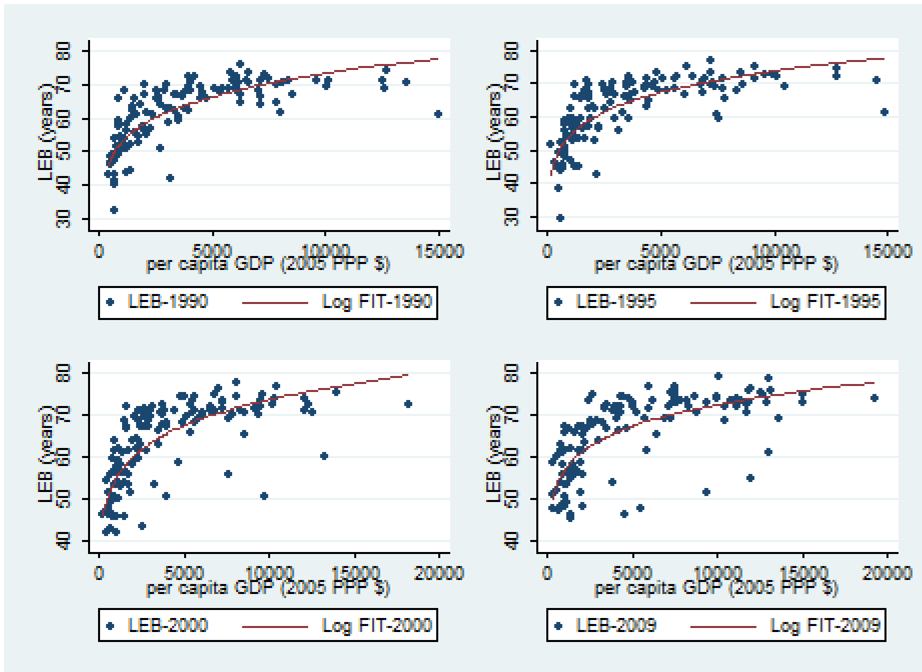

Figure 1: Scatter plot of life expectancy at birth against per capita GDP (2005 PPP $) for 143 developing countries with a bivariate log-log regression curve.

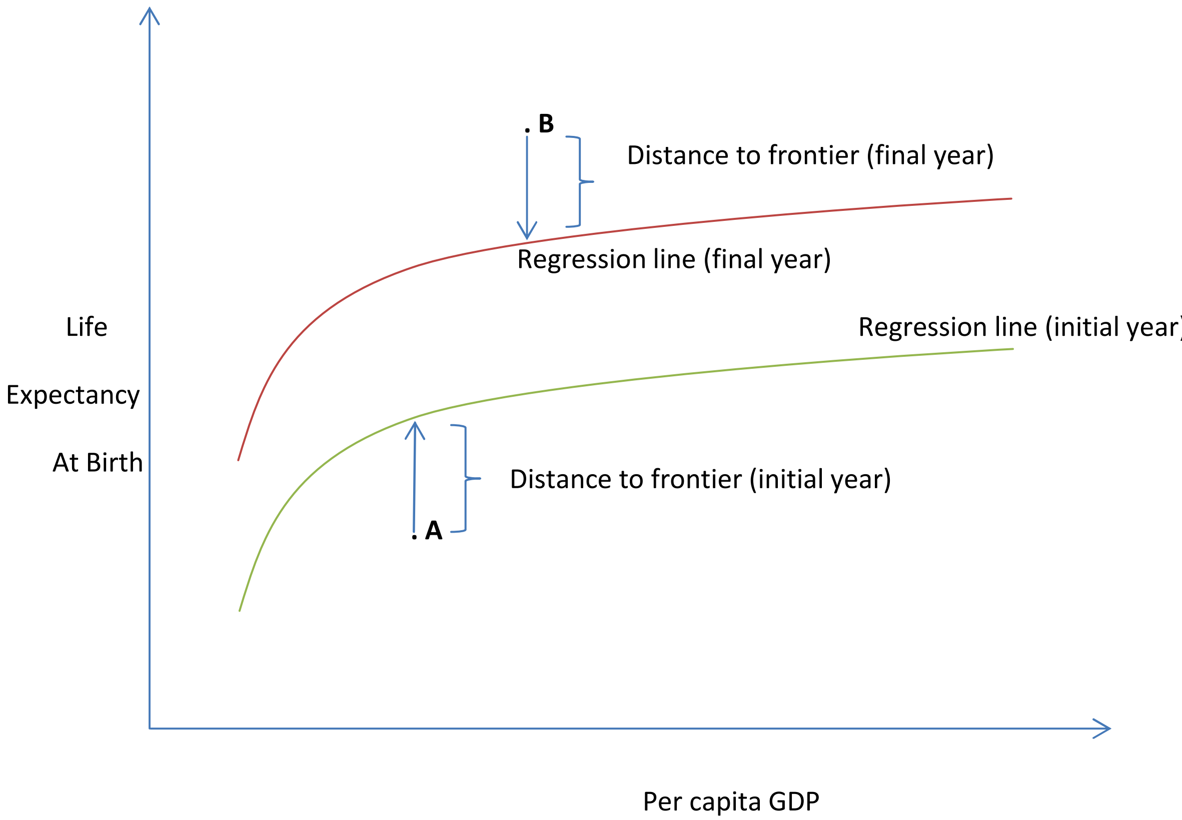

Figure 2: Change in the Distance to Frontier between an initial and a final year. In the initial year, the country occupies position A in the scatter plot (the other countries are not shown in the figure), so that the DTF for the country in the initial year is negative. Thus, the country performs worse than average in the year. In the final year, the country is located in position B, so that its DTF score is positive

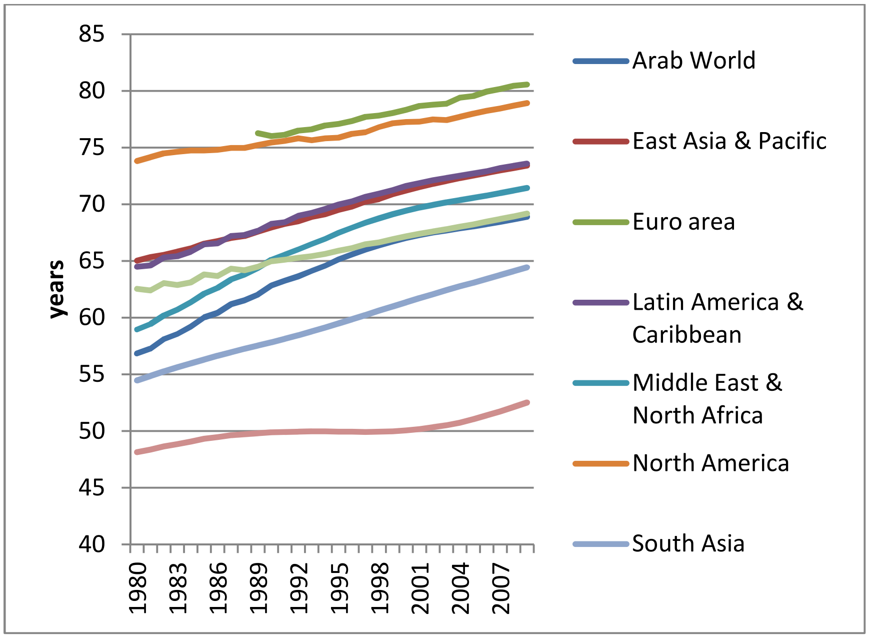

Figure 3: Time series plot of Life Expectancy at Birth (in years) for the main regions of the world.

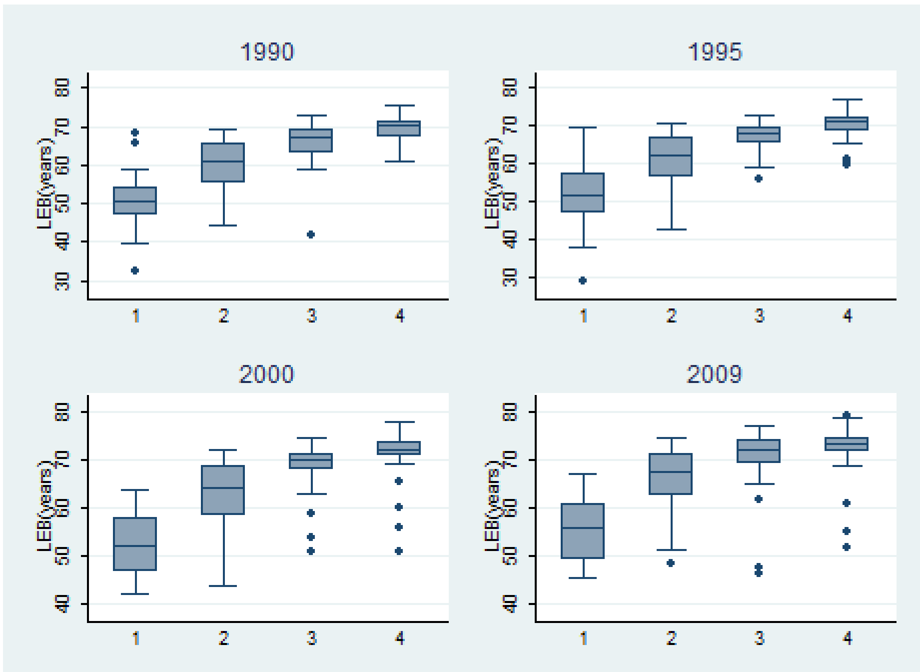

Figure 4: Box plots (minimum, 25th percentile, median, 75th percentile, and maximum) of Life Expectancy at Birth (in years) by quartiles of per capita GDP (2005 PPP $) in 1990, 1995, 2000 and 2009.

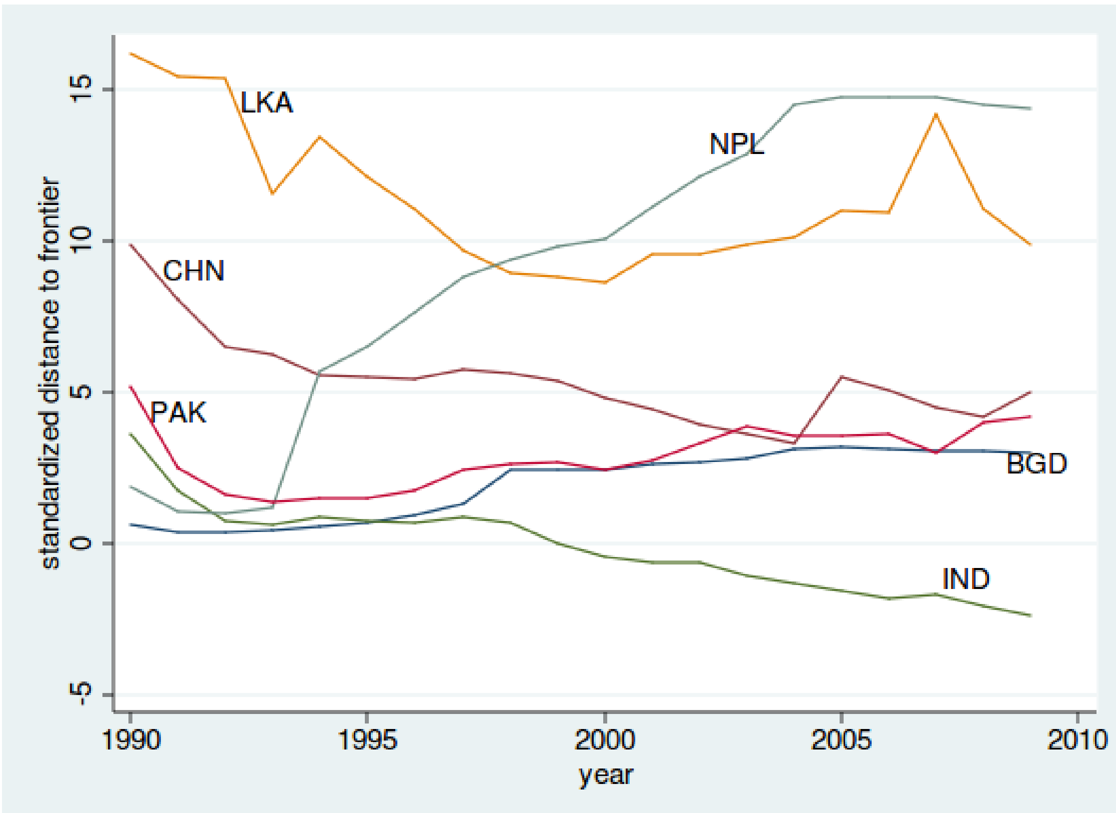

Figure 5: Time series plots of the SDTF metric for the main South Asian countries (BGD: Bangladesh; BTN: Bhutan; IND: India; NPL: Nepal; PAK: Pakistan; LKA: Sri Lanka).

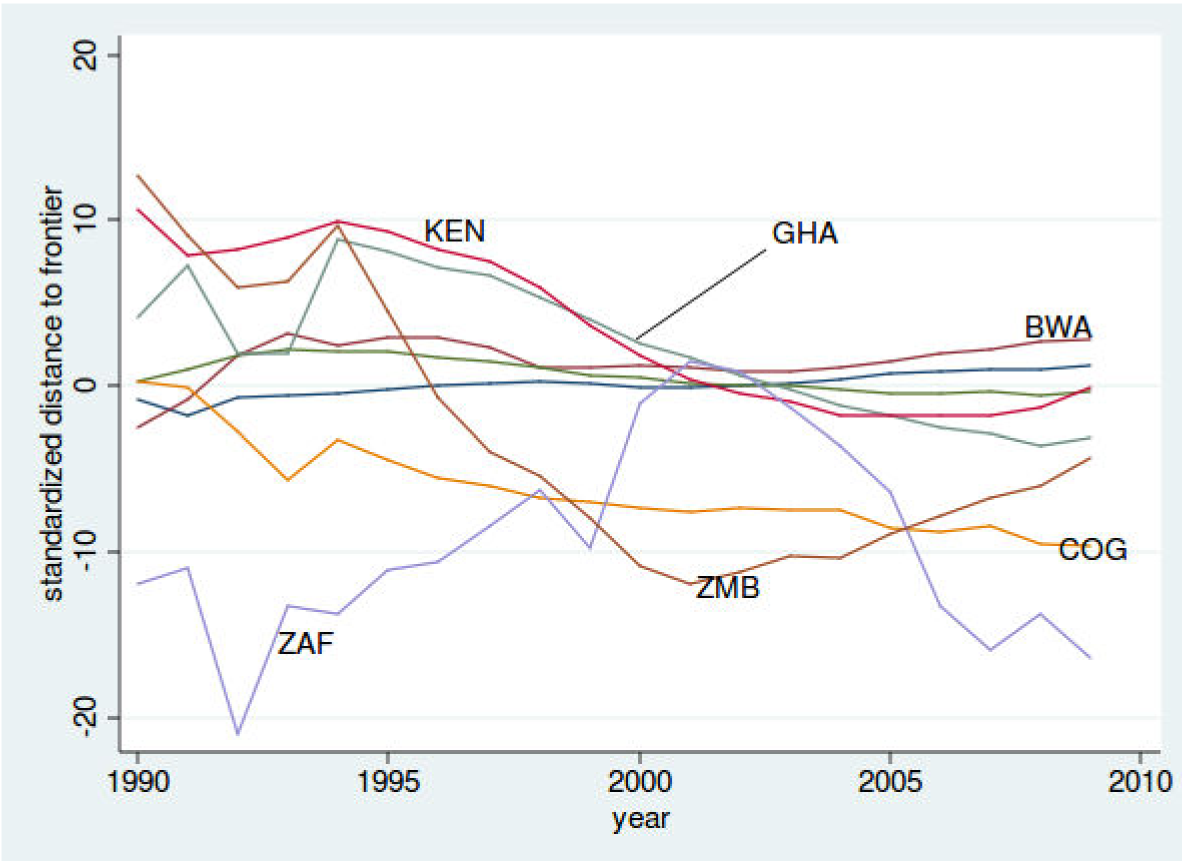

Figure 6: Time series plots of the SDTF metric for some sub-Saharan countries (BWA: Botswana; COG: Republic of Congo; GHA: Ghana; KEN: Kenya; ZAF: South Africa; ZMB: Zambia).

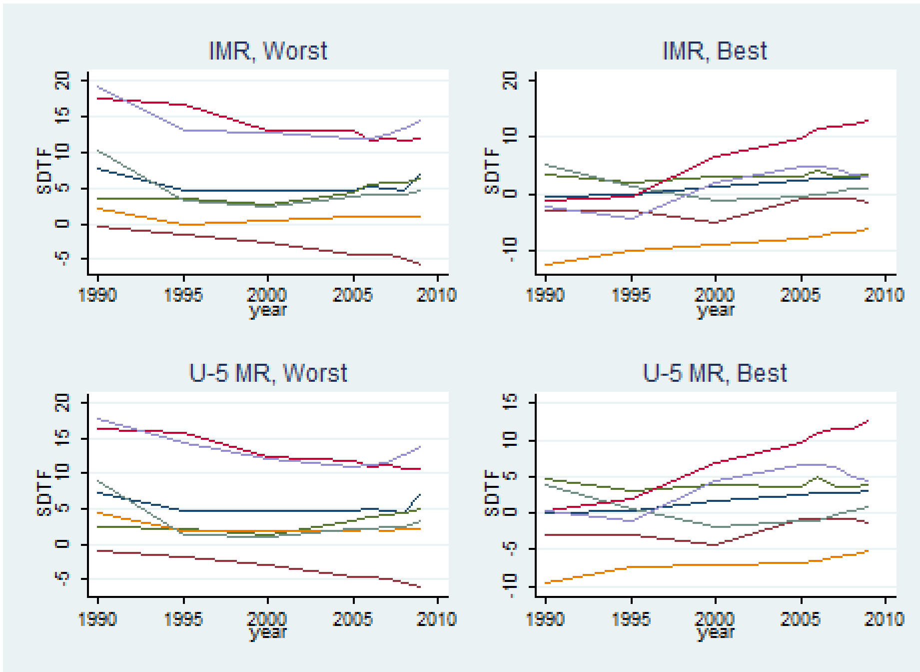

Figure 7: Time series plots of the SDTF metric with respect to IMR and U5MR for the best and worst performing countries (according to relative improvement in life expectancy at birth).