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Relative mortality improvements as a marker of socio-economic inequality across the developing world, 1990-2009

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Relative mortality improvements as a marker of socio-economic inequality across the developing world, 1990-2009

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Abstract: Using cross country regressions, this paper constructs a novel distance-to-frontier metric for tracking broad socio-economic inequality (including 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. To highlight its potential use, the metric is used to rank countries in terms of improvements in socio-economic inequality for the period since 1990. Notable examples of poor performance are displayed by China, Thailand, Kenya and India.

JEL Codes: I14, O57, I32.

Keywords: life expectancy at birth, Preston regression, socio-economic inequality.

1. Introduction

Over the years, the discipline of development economics has gradually moved towards adopting an increasingly inclusive notion of development. Economic development is now seldom understood in purely economic terms as in the initial years of the discipline. For instance, it is now fairly well understood that an exclusive focus on the increase of real per capita GDP is too restrictive a notion of development. As the focus has broadened to include direct indicators of social well-being like life expectancy, infant mortality, maternal mortality, and literacy, two crucial propositions have come to be grudgingly accepted by a wide spectrum of economists and policy makers. On the one hand, it is now recognized that the impact of real per capita GDP growth is quite variable across countries, and regions of the world. On the other hand, it is also understood that non-income factors relating to distribution and public policy crucially impact on social well-being, independent of the effect of income.

One of the widely used direct indicators of social well-being is life expectancy at birth (LEB, henceforth), a summary measure of mortality of a human population. It is defined, for a given time period (usually

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year), as the number of years a newly born child can be expected to live on average if age and sex specific mortality rates of the population in question remain unchanged.¹ Its usefulness and popularity can be easily gauged from its extensive use by economic historians, demographers, development economists, policy makers and political activists alike. Along with indicators like the infant mortality rate (IMR) and under-5 mortality rate (U5MR), LEB provides valuable information about the overall health status of a population.

Figure 1 gives scatter plots of LEB against per capita GDP (measured at 2005 PPP \$) for a group of 135 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 GDP.

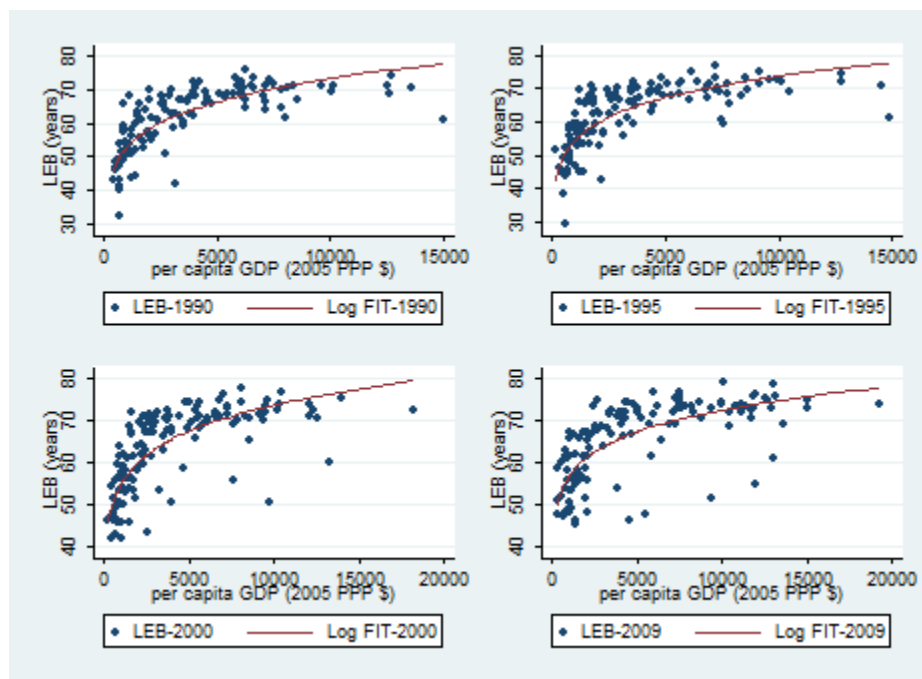


Figure 1: Scatter plot of life expectancy at birth against per capita GDP (2005 PPP \$) for 135 developing countries with a bivariate log-log regression curve.

The scatter plots, with the regression curve embedded in them, depict two well-known facts about the income-health relationship. First, there is a positive relationship between per capita income and LEB:

¹ The *Encyclopedia of Death and Dying* explains how LEB is computed: “Statistics on life expectancy are derived from a mathematical model known as a life table. Life tables create a hypothetical cohort (or group) of 100,000 persons (usually of males and females separately) and subject it to the age-sex-specific mortality rates (the number of deaths per 1,000 or 10,000 or 100,000 persons of a given age and sex) observed in a given population. In doing this, researchers can trace how the 100,000 hypothetical persons (called a synthetic cohort) would shrink in numbers due to deaths as they age. The average age at which these persons are likely to have died is the life expectancy at birth.” It is available online at: <http://www.deathreference.com/>; and, an example of a Life Table is available from the US Social Security Administration here: <http://www.ssa.gov/oact/STATS/table4c6.html>

countries with higher per capita income, on average, have higher LEB. Second, the relationship between per capita income and LEB is essentially nonlinear, with the marginal impact of income growth on LEB improvement tapering off as per capita income levels rise. There is a huge and growing body of literature that has studied various aspects of this relationship (Behrman and Deolalikar, 1988; Anand and Ravallion, 1993; Pritchett and Summers, 1996; Strauss and Thomas, 1998; Bhargava, 2001; Deaton, 2001; Pritchett and Viarengo, 2011).

One interesting aspect of the income-health relationship captured by the scatter plots is the enormous variation of LEB with per capita income. Figure 2 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 2 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).

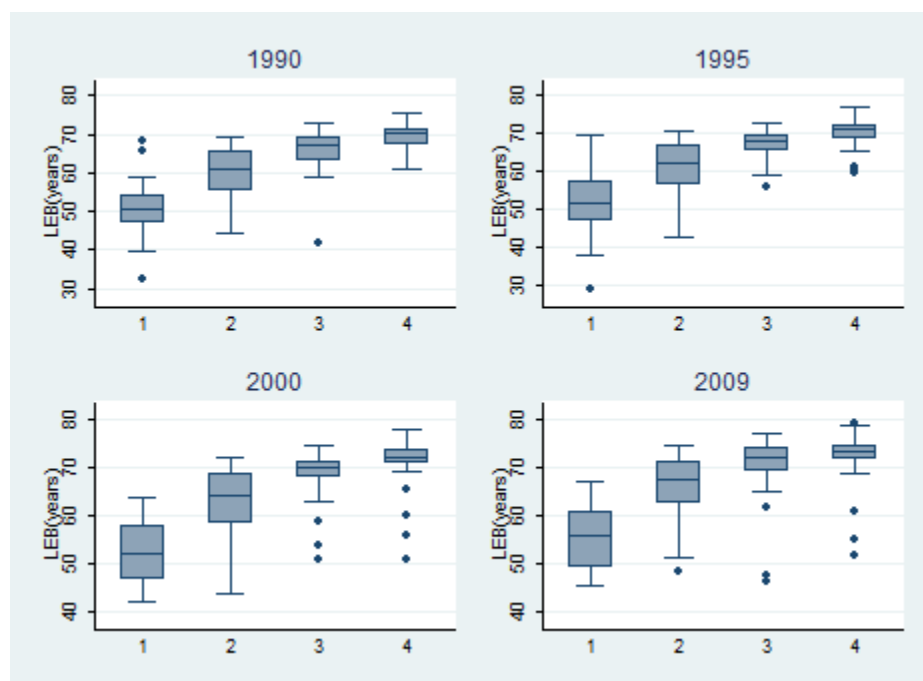


Figure 2: Box plots (minimum, 25th percentile, median, 75th percentile, and maximum) of Life Expectancy at Birth (in years) by quartiles of per capita GDP (2005 PPP \$) in 1990, 1995, 2000 and 2009.

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 undernutrition, 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 2, 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.

To highlight and utilize information contained in the variation of LEB across income classes, 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. Hence, the variations of LEB around the regression curve at a

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”.

given level of per capita income, i.e., the variation of the DTF for any level of per capita income, capture the effects of all non-income factors that affect LEB. Following the finding in the literature about the importance of non-income factors that impinge on LEB, all these non-income factors *taken together* can be fruitfully understood as a measure of broad socio-economic equality. 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 3.

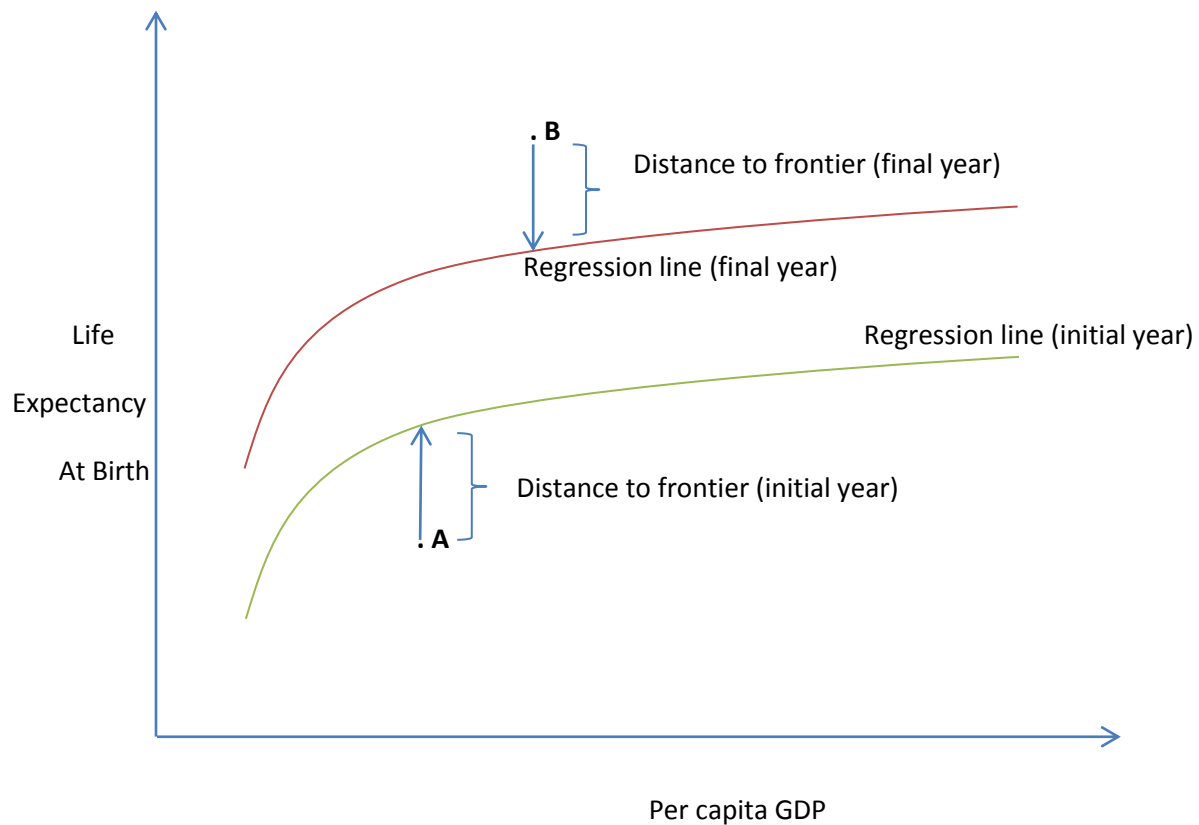


Figure 3: Change in the Distance to Frontier between an initial and a final year. In the initial year, the country occupies position A in the scatter plot (the other countries are not shown in the figure), so that the DTF for the country in the initial year is negative. Thus, the country performs worse than average in the year. In the final year, the country is located in position B, so that its DTF score is positive

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.³ 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 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, which I have called the DTF, 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 DTF 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 DTF might not, in any given year, provide a very accurate measure of socio-economic inequality. But *trends in DTF (or changes in the DTF 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 DTF over time (or focus on the trend in the time series of DTF for any country).⁴ Thus, changes in DTF 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 DTF (the 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 DTF captures the effect of all non-income factors that impact on health outcomes, changes in DTF will necessarily be only a crude measure of changes in socio-economic inequality. While it seems

³ 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.

⁴ The effects of random shocks can be removed by averaging across time for every country. The time series plots of DTF, 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.

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 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.⁵ 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.⁶

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

⁵ For an introduction to these data issues in the context of India, see Deaton and Kozel (2005).

⁶ 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.

positive impact of income growth on living standards, especially of the poor. Conversely, 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.

The rest of the paper is organized as follows. Section 2 develops the distance to frontier metric of mortality improvement and provides intuition behind the claim that the metric can be used to measure broad socio-economic inequality. Section 3 introduces the data, presents results from cross country regressions, and evidence from some panel data fixed effects regressions to show that the DTF metric might be a useful indicator of socio-economic inequality. To illustrate the potential use of the metric, in section 4, I provide a ranking of 98 developing countries in terms of improvements of socio-economic inequality for the period 1990-2009, and also depict trends in the DTF for some countries in South Asia, sub Saharan Africa, Middle East and North Africa, and Latin America. Section 5 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

Building on the pioneering work of Preston (1975), a fairly extensive body of research has investigated the determinants of cross sectional and time series patterns of variations in LEB. This body of research has highlighted the following findings: (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 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.⁷

The bivariate cross-country log-log regression between log-LEB (dependent variable) and log-PCI has been referred to in the literature as the Preston regression; the multivariate analog, i.e., the multivariate log-log regression with additional controls has been called the Augmented Preston regression. The nonlinear relationship between LEB and PCI is sometimes also captured by using a quartic regression. The advantage of the latter is that it allows the income elasticity of LEB to vary with the level of income;

⁷ 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 log-log formulation, on the other hand, imposes a constant income elasticity of LEB across income levels. The disadvantage is that interpretation of any coefficient becomes more complicated. Choosing ease of interpretation over flexibility of the elasticity, in this paper, I will use a log-log specification.

We are interested in developing a metric of changes in socio-economic inequality by studying improvements in LEB over *periods of time* (years, say). To facilitate the discussion, let us denote a Preston regression for the initial year (year t) as

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

where LLEB refers to the natural logarithm of life expectancy at birth (measured in years), $LPCI$ denotes the natural logarithm of PPP-adjusted real per capita income (measured in 2005 international dollars), ε refers to an error term and i ($= 1, 2, \dots, n$) indexes countries, with n representing the sample size. The predicted log LEB, using ordinary least squares (OLS) estimates for the parameters is given for country i for year t by

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

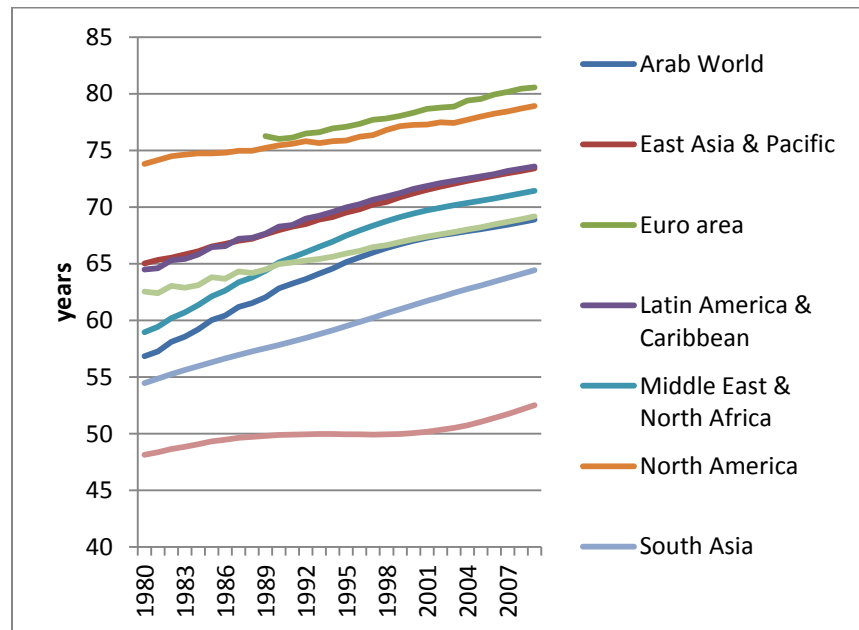


Figure 4: Time series Life Expectancy at Birth (in years) for the main regions of the world.

Let us refer to the regression curve as the “medical technology frontier”. This terminology is meant to indicate the following: given the per capita income of any country, the regression curve gives the level of LEB it can expect to achieve on average because of medical technological resources available to all countries. This means that, for any country, the distance from the regression curve for any year measures the performance of that country *relative to* the cross-country “average” performance. Let us call this distance, measured in years (or log-years), the “distance to frontier” (DTF). Note that if the DTF is positive for any country in a given year then the country can be seen as having performed better than the average in that year; if it is negative, the country performed worse than average.

Figure 4 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. Thus, the augmented Preston regression that we use in this paper uses both per capita income and the prevalence of HIV as regressors:

$$(3) \quad LLEB_{it} = \alpha_t + \beta_t \times LPCI_{it} + \gamma_t \times HIV_{it} + \varepsilon_{it},$$

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

$$(4) \quad \widehat{LLEB}_{it} = \hat{\alpha}_t + \hat{\beta}_t \times LPCI_{it} + \hat{\gamma}_t \times HIV_{it}.$$

Since we are interested in investigating aspects of socio-economic inequality and its relationship to health outcomes, it might appear that we should include a variable capturing income (or wealth) inequality in the cross country regression. We do not do so for two reasons. First, we would like to collect together the effects of all non-income factors that affect health into one portmanteau measure given by the residual of the regression; since we want income (or wealth) inequality to be in this portmanteau measure, we do not include it as a regressor. Second, data on income (or wealth) inequality is not readily available for developing countries. As we have already indicated, between 1990 and 2009, the best case scenario has data on income distribution only for a fourth of the countries. If we were to include income distribution as a regressors, our sample size would shrink rather drastically, by as much as 94 percent in certain years.

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

$$(5) \quad DTF_{it} = LLEB_{it} - \widehat{LLEB}_{it} = \hat{\varepsilon}_{it},$$

where hat-quantities denote predicted values computed from the regression.

Comparing $LLEB$ for any country i at two points in time, an initial year t and some later year T , we see that

$$(6) \quad LLEB_{iT} - LLEB_{it} = (\hat{\alpha}_T - \hat{\alpha}_t) + (DTF_{iT} - DTF_{it}) + \{(\hat{\beta}_T \times LPCI_{iT} + \hat{\gamma}_T \times HIV_{iT}) - (\hat{\beta}_t \times LPCI_{it} + \hat{\gamma}_t \times HIV_{it})\}.$$

This shows that the observed changes in LLEB can be decomposed into three parts. The first comes from progress in medical technology and is captured by $(\hat{\alpha}_T - \hat{\alpha}_t)$. The second comes from increases in per capita income, reduction in HIV prevalence and increases in women's education; this is captured by

$$\{(\hat{\beta}_T \times LPCI_{iT} + \hat{\gamma}_T \times HIV_{iT}) - (\hat{\beta}_t \times LPCI_{it} + \hat{\gamma}_t \times HIV_{it})\}.$$

The third part is the difference in the estimated residuals in the two years $(\hat{\varepsilon}_{iT} - \hat{\varepsilon}_{it})$, and is, thus, the change in the distance to frontier metric.

It is worthwhile considering the three factors in (6) in some detail. With regard to the first factor, the technological factor, it is natural to ask: why does the curve shift over time? Why does technological progress, captured by the term $(\widehat{\alpha}_T - \widehat{\alpha}_t)$, contribute to improvements in LEB over time? Shifts of the curve, what we have referred to as the “medical technology frontier”, over time represents the effects of technological change (relating, for instance to immunization, pre and post natal care, better medical technologies, etc.) and public policy, both of which are socially mediated processes and require conscious intervention. Adoption of the relevant technology and making it widely available across a country requires *public* resources, material and non-material, alike; it is undoubtedly facilitated by activist and progressive public policy of the State.

The second factor in (6),

$$\{(\widehat{\beta}_T \times LPCI_{iT} + \widehat{\gamma}_T \times HIV_{iT}) - (\widehat{\beta}_t \times LPCI_{it} + \widehat{\gamma}_t \times HIV_{it})\},$$

represents the impact of observable covariates that affect the level of LEB. Typically, cross country regressions have incorporated per capita income, prevalence of HIV and other covariates in the set of relevant controls. Per capita income is meant to capture the command over *private* resources of the average household in country *i*. The command over resources is reflected in the nutrition that is available to the household, the quality and quantity of health care services that it can purchase, the level of sanitation that it can provide for itself in its living space, and other similar things that it has to provision for itself. Being a representation of the command over resources of the average household, it naturally glosses over its distribution. HIV prevalence is meant to capture the exogenous impact of the AIDS epidemic that has ravaged countries since the early 1990s, especially the sub-Saharan countries.

Being changes in the regression residual, the third factor captures the impacts of those factors which impact the LEB after medical technology, per capita income, HIV prevalence and women’s education has been accounted for. The basic claim of this paper is that main variable that lies hidden in the third factor in (6) relate to shifts in societal inequality, broadly defined. This includes not only income and wealth distribution, what Sen (1983) refers to as “exchange entitlements”, but also non-income measures of inequality like changes in access to public health resources, provision of local public goods over time. The basic idea behind this claim is straightforward. If there is positive redistribution, i.e., redistribution of income, wealth and (more generally) resources, in favour of the poorer sections of society, that will have a disproportionately large positive impact on LEB (or other similar indicators of living standard). This is because the LEB, being an aggregate indicator, is a weighted average of life expectancy at birth across various income/expenditure classes, with weights proportional to shares of the various income classes in the population. Since life expectancy at birth will be lower at the lower end of the income distribution, improving the life expectancy for *this* group will improve the aggregate measure by much more than if improvement were limited to the richer section of the population. A positive redistribution of income and wealth and an increase in the reach of public health resources to poorer sections will do precisely that and will, therefore, have a disproportionately large positive impact on aggregate measures like LEB.

3. Main Results

3.1 Model and Data

The results in this paper will use an Augmented Preston regression

$$(7) \quad LLEB_{it} = \alpha_t + \beta_t \times LPCI_{it} + \gamma_t \times HIV_{it} + \varepsilon_{it}$$

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 (7) will be estimated for every year between 1990 and 2009. Estimates of the residual will be used to construct the distance to frontier metric, DTF, for every country in the sample. The trend in the DTF metric will then 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 1990-2009.⁸

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 1990.⁹

[TABLE 1]

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 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

⁸ The WDI data base can be accessed here: <http://data.worldbank.org/data-catalog/world-development-indicators>

⁹ The GAPMINDER database can be accessed here: <http://www.gapminder.org/>

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 0.137 in 1990 to 0.125 in 1995 to 0.096 in 2009. Thus, in 1990, every percentage point increase in per capita income would be associated with 0.14 percentage point increase in LEB; in 2009, every percentage point increase in per capita income was associated with only a 0.09 percentage point increase in LEB.

[TABLE 2]

The magnitude of the intercept, again strongly significant, increases from 3.025 to 3.163 to 3.417 over the same period. The increase in the estimated value of the constant 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 -0.01 in 1990 (and 1995) to -0.016 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 year; in 2009, the corresponding reduction was 1.7 years. In the next section, I will use these regression estimates to construct the DTF for every country and year between 1990 and 2009, and use it to construct an improvement metric (IM) that will provide information about the direction of change of socio-economic inequality over time.

3.4 DTF as a measure of socio-economic inequality

In this section, I present some preliminary results in favour of the claim that changes in the DTF 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. The difficulties with testing the claim rest primarily on the reliability of the income distribution data.

[TABLE 3]

To test the relationship of the DTF metric to broad measures of income inequality, public expenditure and the status of women, I run bivariate regressions using a panel data set with data on the DTF metric, the ratio of the income of the top to the bottom quintile, public health expenditure as a share of GDP and enrollment of girls in primary educational institutions. The model I estimate is

$$(8) \quad DTF_{i,t} = \alpha_i + \beta * X_{i,t} + \varepsilon_{i,t},$$

where DTF denotes the DTF metric, X stands, in turn, for income distribution, public health expenditure and female education, α stands for a country-specific fixed effect, i indexes countries and t indexes years. Table 3 presents results of estimating β in (8) using a fixed effect (FE) estimation procedure. Since there is a possibility of endogeneity of the regressors, I also present FE estimates using the lagged regressor as an instrument for the regressor itself.

Public health expenditure and female education have the expected sign with and without instrumenting, and both are statistically significant. Columns (3) and (4) have estimates of the coefficient on public health expenditure (as a share of GDP). The positive estimates indicate that higher public health expenditure leads to a higher value of the DTF metric, and lead to above average (and improving) performance in comparison to other developing countries. The magnitude of the estimate suggest that each percentage point increase in public health expenditure leads to an increase in the DTF between 0.2 and 0.3 years. The coefficient on female education has a similar interpretation: every percentage point increase in female enrollment leads to an improvement in the DTF metric by about 0.02 years. Thus, the impact of public health expenditure seems to be an order of magnitude higher than female education.

The coefficient on the income inequality measure – the ratio of the income share of the top to the bottom quintile – has an unexpected positive sign in column (1). This might be cause of several reasons. First, it might be that there is severe mis-measurement in the income share ratio. Since it is well known that top income shares are severely underestimated in sample surveys, this might bias the measure of income inequality and lead to incorrect results. Second, the income inequality measure might be endogenous in the sense that both income inequality and the DTF metric might be impacted by another factor. For instance, a policy shift against redistribution would have an impact on both income distribution (because of changes in tax policies, say) and the relative performance related to LEB improvement (because of reduction in the financing of nutrition programs, say). To take account of these problems, column (2) presents FE estimates of the coefficient on income distribution where a one period lag of income distribution is used to instrument income distribution. The estimate in column (2)

has the expected negative sign and the magnitude of the estimate suggests that every percentage point increase in the ratio of the income share of the top to the bottom quintile leads to a deterioration of the DTF metric by 0.2 years. The magnitude of the effect of income inequality, thus, seems of the same order of magnitude as public health expenditure.

4. Applications

To illustrate the use of the DTF metric, I will use it to compute improvements in LEB between 1990 and 2009 for a set of 135 countries. Recall that for country i , the distance to the frontier in the initial year (1990, say) can be written as

$$(9) \quad DTF_{it} = LLEB_{it} - \widehat{LLEB}_{it} = \hat{\varepsilon}_{it},$$

where hat-quantities denote predicted values computed from the regression curve. In a similar manner, the distance to frontier in the final year (year T , 2009 in our case) is

$$(10) \quad DTF_{iT} = LLEB_{iT} - \widehat{LLEB}_{iT} = \hat{\varepsilon}_{iT}.$$

Comparing the DTF for any country between the two years, final and initial, we can arrive at a metric of improvement over time that controls for country-specific income growth, “exogenous” progress in medical technology that is potentially available to all countries to adopt, and HIV prevalence rates. Denoting this improvement metric as IM , its value for any country i between periods T (final period) and t (initial period) can be written as:

$$(11) \quad IM_{T,t}^i = DTF_{iT} - DTF_{it} = (\hat{\varepsilon}_{iT} - \hat{\varepsilon}_{it}).$$

I have argued in this paper that such an improvement metric can also be used as a measure of *changes* in socio-economic inequality. While a positive value of IM in (11) denotes movement in the direction of greater equality (i.e., improvement) and a negative value denotes movement in the direction of greater inequality (i.e., deterioration) over the relevant time period, it is worthwhile distinguishing at least four interesting cases.

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

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

Case 3 (negative persistence): the country is below average in the initial year ($DTF_{it} < 0$) and continues to remain so in the final year ($DTF_{iT} < 0$); 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 $DTF_{it} < DTF_{iT} < 0$.

Case 4 (positive persistence): the country is above average in the initial year ($DTF_{it} > 0$) and continues to remain so in the final year ($DTF_{iT} > 0$); 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 $0 < DTF_{iT} < DTF_{it}$.

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 improvement occurring due to positive redistribution leading to a decline in socio-economic inequality.

4.1. World Ranking of Improvement in Socio-Economic Inequality, 1990-2009

Table 4 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 using HIV prevalence as the only control.¹⁰ Higher rankings go with lower improvement scores, i.e., value of IM , and thus indicate worse performance. Table 5 provides the list of countries which witnessed either positive or negative switch between 1990 and 2009.

Two countries which have grown very rapidly since the 1990s but have not managed to translate that rapid economic growth into improvements in LEB are China and India. Both countries figure towards the very end of the list of rankings; India is ranked 88 and China 98 among 98 countries for whom the ranking is provided in Table 4. This indicates that the growth process underway in both countries must have worsened socio-economic inequality significantly.¹¹

It might be thought that the improvement metric is biased against countries that have registered high growth. This is not the case for two 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. Thus, the improvement metric already accounts for the fact that marginal increases in LEB calls for higher income growth as LEB increases.

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, 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

¹⁰ Women's education (girl's primary enrollment rates) data is available for only about 50 countries for both 1990 and 2009. To keep the sample as large as feasible, I did not use women's education as a control.

¹¹ For evidence on wealth inequality in India after the 1990s, see Bannerjee and Piketty (2005), and Jaydev, Motiram and Vakulabharanam (2007); for evidence on widening inequalities in China, see Hart-Landsberg (2011).

GDP and also witnessed worsening socio-economic inequality. Examples of such countries are Central African Republic, Kenya, and Zambia.

[TABLE 4]

The case of India is especially worrisome because it also figures in the list of 13 countries, along with Ghana, Kenya, Thailand, Belarus, Zambia, Uganda, Lebanon, Bulgaria, Mauritius, Malaysia, Suriname, and Cote d'Ivoire, 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 worst performing states are Sri Lanka (at rank 89/98) and Costa Rica (at rank 68/98). These cases certainly require 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.

4.2. Divergent Country Performances, 1990-2009

Figures 5, 6, 7 and 8 plot the DTF for groups of countries in South Asia, sub Saharan Africa, middle East & North Africa and Latin America. The most striking feature of the time series plots of DTF is the visible lack of random fluctuations in the year to year movement of DTF for each country; hence, the effect of random shocks in driving the movement of DTF over time seems to be rather attenuated, if at all present. In fact, the DTF metric for each country displays a smooth movement and strong persistence over time.

[TABLE 5]

Divergent performance of countries in the same region, as depicted in Figure 5, 6, 7 and 8, reinforce the case for using changes in DTF as a relatively accurate marker of the direction of change of 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 DTF metric has already controlled for per capita income and medical technological change, divergent movements of the DTF among countries in the same region must be driven by the whole host of non-income factors that impact on socio-economic inequality.

4.2.1. 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 the 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.

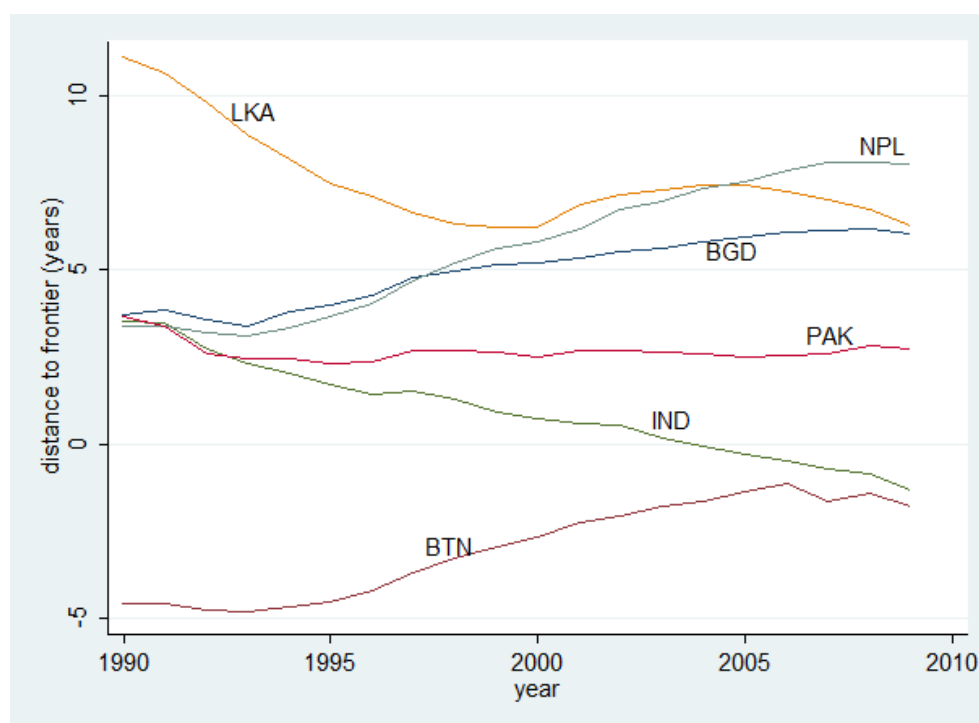


Figure 5: Time series plots of the DTF metric for the main South Asian countries (BGD: Bangladesh; BTN: Bhutan; IND: India; NPL: Nepal; PAK: Pakistan; LKA: Sri Lanka). The DTF metric is the value of the residual in a cross country regression of log life expectancy at birth on a constant, log per capita GDP and HIV prevalence. Trends in the DTF metric provide information about the direction of change in socio-economic inequality, an increasing (positive) trend indicating reductions in socio-economic inequality and vice versa.

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.

4.2.2. 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.

4.2.3. Middle East and North Africa

Figure 7 plots the DTF metric for the period 1990-2009 for some countries in the Middle East and Northern Africa. Among the countries selected for Figure 7, Algeria show a steady and significant improvement over time, switching from a below average to an above average performing country. Tunisia, on the other hand, has witnessed a steady deterioration, even though it remains an above average performer throughout the period. While Iran has improved its relative position since the mid-1990s, it still remains below the frontier. Egypt and Morocco has witnessed their trajectory of steady improvement being stalled by the late-1990s.

4.2.4. Latin America

Figure 8 presents time series plots of the DTF for some countries in Latin America. The most striking aspect of Figure 8 is the general upward trajectory of DTF since the mid-1990s for all the countries in the region. This is in sharp contrast to the divergent trends seen among countries in South Asia, sub Saharan Africa, and Middle East & North Africa. Within this picture of general improvement, there are interesting differences.

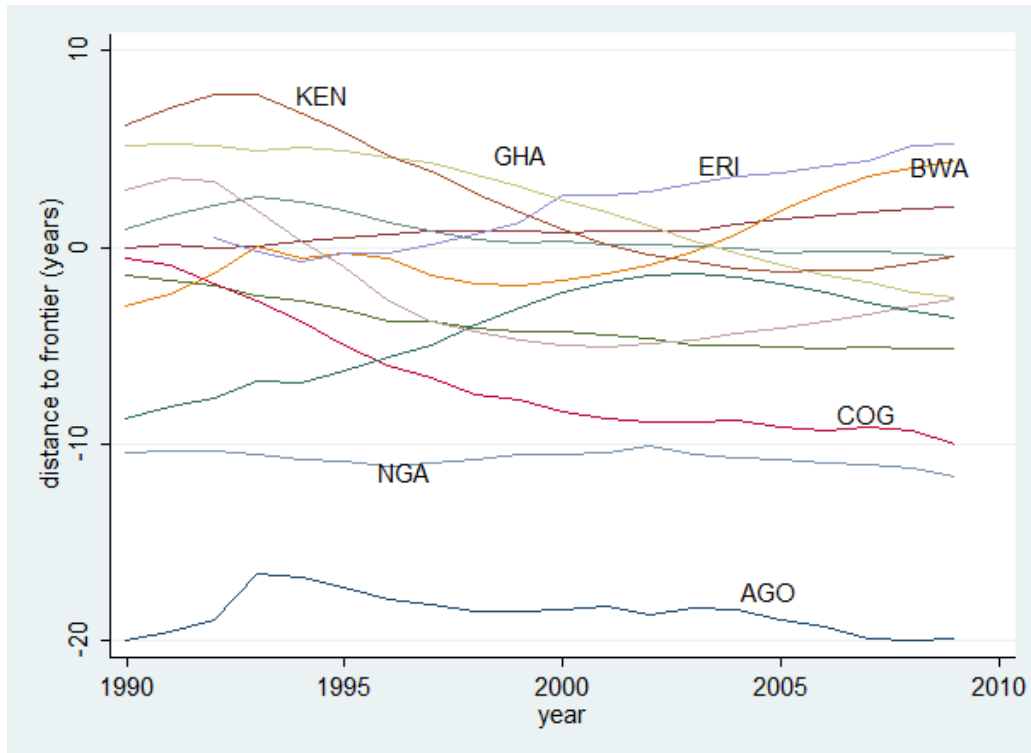


Figure 6: Time series plots of the DTF metric for some sub-Saharan countries (AGO: Angola; BWA: Botswana; COG: Republic of Congo; ERI: Eritrea; GHA: Ghana; KEN: Kenya; NGA: Nigeria). The DTF metric is the value of the residual in a cross country regression of log life expectancy at birth on a constant, log per capita GDP and HIV prevalence. Trends in the DTF metric provide information about the direction of change in socio-economic inequality, an increasing (positive) trend indicating reductions in socio-economic inequality and vice versa.

Brazil, Bolivia, Ecuador and Guatemala have witnessed steady improvements in socio-economic inequality. Brazil and Bolivia were both below average performers in the early 1990s; Brazil has become an average performer, while Bolivia, despite steady improvement, continues to be a laggard. Guatemala was just below average in 1990; steady improvement since then has made it an above average performer.

Two countries which have not seen much improvement over the whole period are Chile and Argentina. Both these countries witnessed a U-shaped movement since 1990, with a period of deterioration being followed by improvement. The trajectory of improvement in Argentina seems to have been stalled since the mid-2000s.

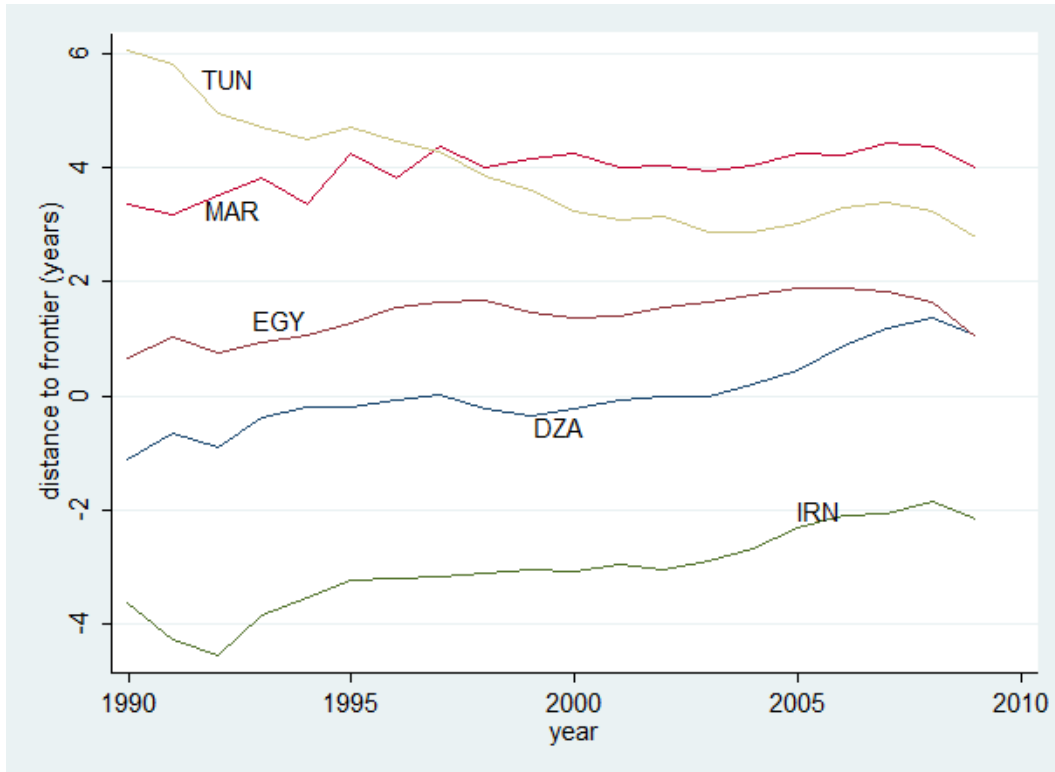


Figure 7: Time series plots of the DTF metric for some countries in Middle East and North Africa (DZA: Algeria; EGY: Egypt; IRN: Iran; MAR: Morocco; TUN: Tunisia). The DTF metric is the value of the residual in a cross country regression of log life expectancy at birth on a constant, log per capita GDP and HIV prevalence. Trends in the DTF metric provide information about the direction of change in socio-economic inequality, an increasing (positive) trend indicating reductions in socio-economic inequality and vice versa.

5. Robustness Checks

The DTF 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 DTF metric can be used as a measure of the direction of change in socio-economic inequality. Is the DTF metric robust to the indicator of living standard?

To evaluate the robustness of the DTF 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 DTF 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 DTF 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 DTF metric implies below average performance.

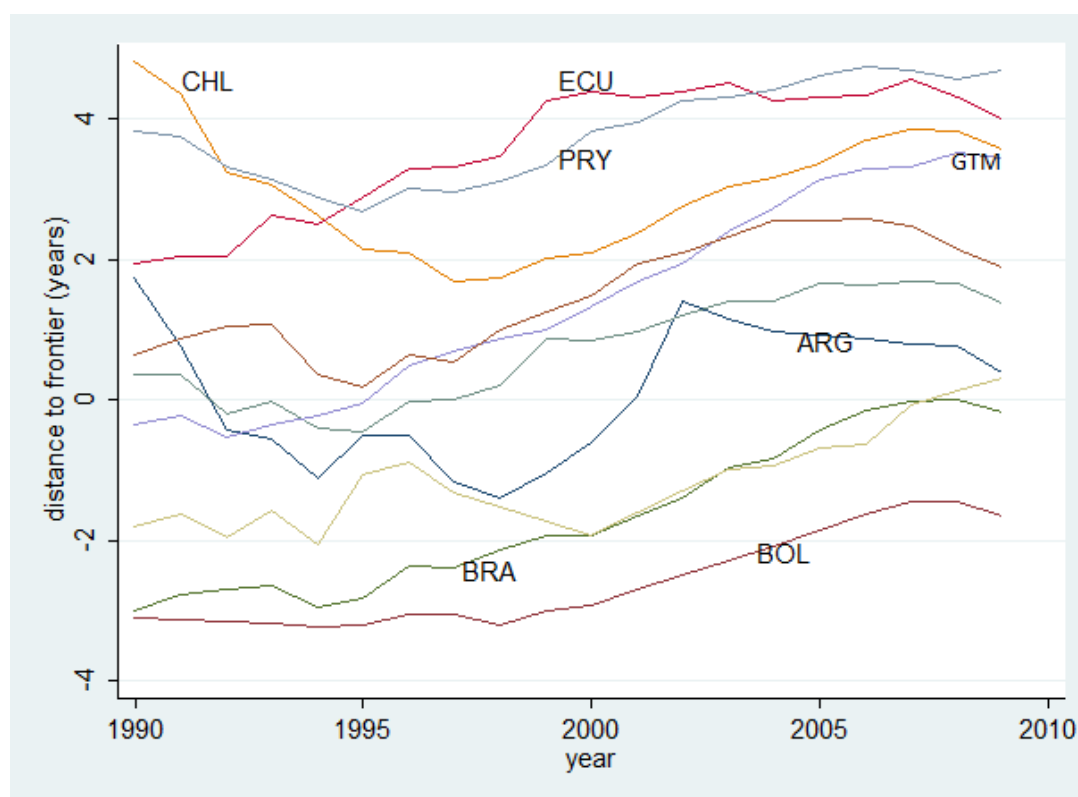


Figure 8: Time series plots of the DTF metric for some countries in Latin America (ARG: Argentina; BOL: Bolivia; BRA: Brazil; CHL: Chile; ECU: Ecuador; GTM: Guatemala; PRY: Paraguay). The DTF metric is the value of the residual in a cross country regression of log life expectancy at birth on a constant, log per capita GDP and HIV prevalence. Trends in the DTF metric provide information about the direction of change in socio-economic inequality, an increasing (positive) trend indicating reductions in socio-economic inequality and vice versa.

Figure 9 plots the DTF 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 low ranks in Table 4), and (b) those that have shown large deterioration of socio-economic inequality in the 1990-2009 period (and have high ranks in Table 4). The countries in the first group are: India, China, Ghana, Kenya, Thailand, Republic of Congo, Chad and Sri Lanka; the countries in the second group: Algeria, Bangladesh, Brazil, Guatemala, Nepal, South Africa, and Namibia.

The charts on the right column in Figure 9 show that, in general, the countries that displayed large improvements in socio-economic inequality with respect to the DTF metric on LEB, i.e., countries in the first group, have also performed well with respect to the DTF metric on IMR and U5MR. This is because

the DTF metric with respect to both IMR and U5MR (charts on the right column in Figure 9) increase over time between 1990 and 2009; the only exception seems to be South Africa.

Similarly, the charts on the left column in Figure 9 show that, again in general, the countries that displayed large deterioration in socio-economic inequality with respect to the DTF metric on LEB, i.e., countries in the second group, have also performed worse with respect to the DTF metric on IMR and U5MR. This can be seen from the charts in the left column of Figure 9, where the DTF metric either declines over time, or remains flat. No country in this group shows an increase in the DTF metric over time. Hence, the DTF metric with respect to both IMR and U5MR show expected movements. Thus, the DTF metric seems to be minimally robust to the chosen indicator of living standard.

6. Conclusion

This paper has argued that relative improvements in life expectancy at birth (LEB) across countries can 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 DTF for a range of countries across South Asia, sub Saharan Africa, Middle East & North Africa, and Latin America. Countries which have witnessed worsening inequality, with or without economic growth, have also performed poorly when ranked by the distance to frontier (DTF) metric; notable examples of countries which witnessed rapid economic growth but worsening socio-economic inequality are China, India, and Thailand.

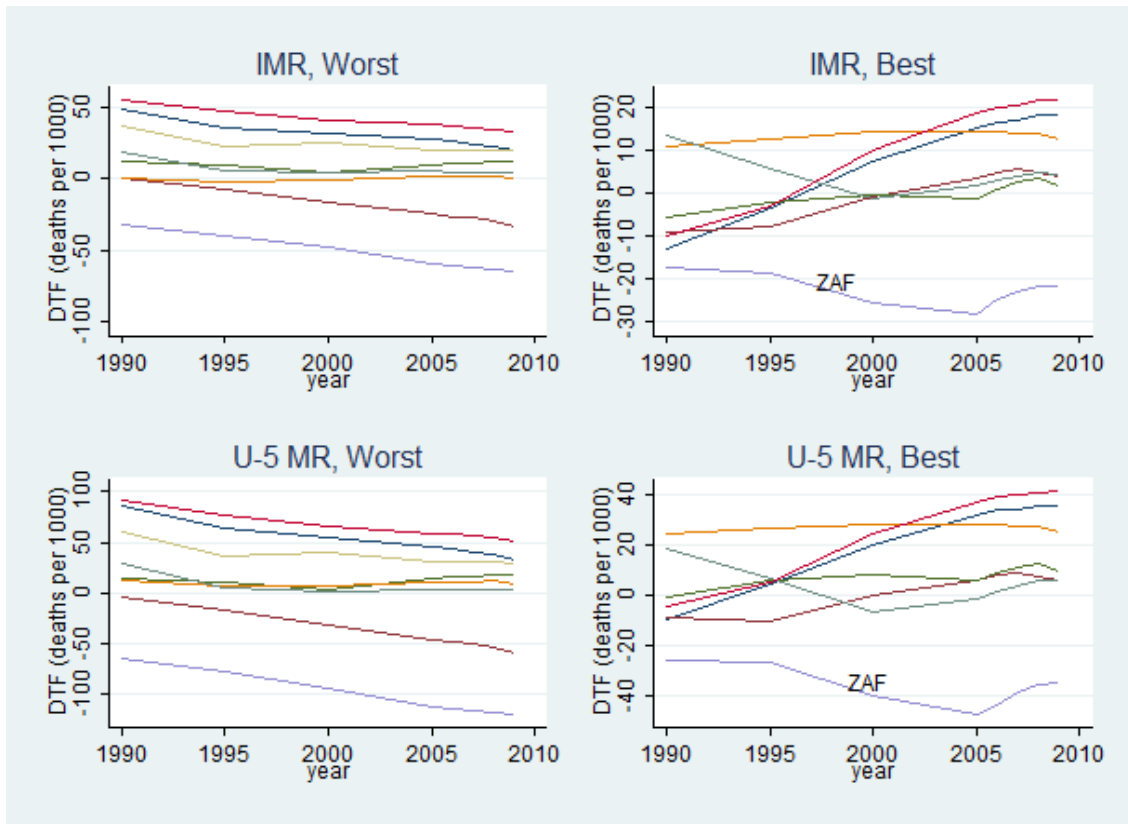


Figure 9. Time series plots of the DTF metric for IMR and U5MR for two sets of countries. First group: India, China, Ghana, Kenya, Thailand, Republic of Congo, Chad and Sri Lanka; these countries displayed large deterioration of socio-economic inequality between 1990 and 2009 as measured by change in the DTF for LEB (Table 4). Second group: Algeria, Bangladesh, Brazil, Guatemala, Nepal, South Africa, and Namibia.

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 DTF 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.

References

- Anand, S., and M. Ravallion. 1993. "Human development in poor countries: On the role of private incomes and public services," *Journal of Economic Perspectives*, 7(1): 133-50.
- Banerjee, A., and T. Piketty. 2005. "Top Indian Incomes, 1922-2000," *The World Bank Economic Review*, 19 (1): 1-20.
- Barro, R., and J. W. Lee. 2001. "International Data on Educational Attainment. Updates and Implications," *Oxford Economic Papers*, 53 (3): 541-63.
- Caldwell, J. C. 1986. "Routes to low mortality in poor countries," *Population and Development Review*, 12(2): 171-220.
- Deaton, A., and V. Kozel. 2005. *The Great Indian Poverty Debate*. Macmillan India Ltd.: Delhi.
- Dreze, J. 2004. "Bangladesh shows the way," *The Hindu*, September 17. (Available here: <http://www.hindu.com/2004/09/17/stories/2004091701431000.htm>)
- Dreze, J., and A. Sen. 1991. *Hunger and Public Action*. Oxford University Press: London.
- Hart-Landsber, M. 2011. "The Chinese Reform Experience: A Critical Assessment," *Review of Radical Political Economics*, 43(1): 56-76.
- Hill, M.A., and E. M. King. 1995. "Women's education and economic well-being," *Feminist Economics*, 1(2): 21-46.
- Husain, A. R. 2002. "Life expectancy in developing countries: A cross-section analysis," *The Bangladesh Development Studies*, 28(1&2).
- Jaydev, A., S. Motiram and V. Vakulabharanam. 2007. "Patterns of Wealth Disparities in India during the Liberalization Era," *Economic and Political Weekly*, 22 September, pp. 3853-63.
- Macfarlane, S., M. Racelis, and F. Muli-Muslime. 2000. "Public health in developing countries," *Lancet*, 356: 841-46. DOI: 10.1016/S0140-6736(00)02664-7
- Mahfuz, K. 2008. "Determinants of life expectancy in developing countries," *Journal of Developing Areas*, 41(2): 185-204.
- Meisner, M. 1999. "The significance of the Chinese revolution in world history," Working Paper, Asia Research Center, London School of Economics and Political Science, London, UK.
- Pandey, M.D., and S. Nathwani. 1997. "Measurement of Socio-Economic Inequality using the Life-Quality Index," *Social Indicators Research*, 39: 187-202.

Preston, S. H. 1975. "The Changing Relation between Mortality and Level of Economic Development," *Population Studies*, 29 (2): 231-48.

Pritchett, L., and M. Viarengo. 2010. "Explaining the Cross-National Time Series Variation in Life Expectancy: Income, Women's Education, Shifts, and What Else?" United Nations Development Programme, Research Paper 2010/31.

Ryan, M. 1988. "Life expectancy and mortality data from the Soviet Union," *British Medical Journal*, 296: 1513-15.

Sen. A. 1983. *Poverty and Famines: An Essay on Entitlement and Deprivation*. Oxford University Press: New York.

Sen. A. 2001. *Development as Freedom*. Alfred A. Knopf: New York.

Sen, A. 2011. "Growth and other concerns," *The Hindu*, February 14. (Available here: <http://www.thehindu.com/opinion/op-ed/article1451973.ece?homepage=true>)

Sugiura, Y., Ju, Y.S., Yasuoka, J., and M. Jimba. 2010. "Rapid increase in Japanese Life Expectancy after World War II," *Biosci Trends*, 4(1): 9-16.

Williamson, J.B. and U. Boehmer. 1997. "Female life expectancy, gender stratification and level of economic development: a cross national study of less developed countries," *Social Science and Medicine*, 45(2): 305-17.

Wilkinson, R., and K. Pickett. 2006. "Income inequality and population health: a review and explanation of the evidence," *Social Science and Medicine*, 62(7): 1768-84.

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 \$)	0.137***	0.124***	0.117***	0.0959***
	(11.26)	(10.36)	(12.22)	(11.48)
HIV PREVALENCE (% of 15-49)	-0.0100	-0.0104**	-0.0136***	-0.0159***
	(-1.85)	(-3.30)	(-7.67)	(-9.49)
CONSTANT	3.025***	3.163***	3.234***	3.417***
	(30.90)	(33.35)	(42.35)	(49.64)
N	97	102	102	103
adj. R-sq	0.625	0.584	0.698	0.707

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

Table 3: Panel Regression Results

	DEP VAR: DISTANCE TO FRONTIER					
	(1)	(2)	(3)	(4)	(5)	(6)
INCOME SHARE OF TOP TO BOTTOM QUINTILE	0.0431** (3.29)	-0.214* (-2.39)				
PUBLIC HEALTH EXPENDITURE (% OF GDP)			0.228*** (4.30)	0.362*** (5.12)		
FEMALE PRIMARY ENROLLMENT (%)					0.0215*** (4.65)	0.0236*** (4.34)
CONSTANT	0.510** (3.02)		-0.395** (-2.69)		-1.175** (-3.25)	
INSTRUMENTAL VARIABLE	N	Y	N	Y	N	Y
N	438	72	1537	1434	930	713
R-sq	0.031	0.038	0.013	0.003	0.025	0.019

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

Table 4: Ranking of Countries by Improvement Metric, 1990-2009

Rank	Country	IM	Rank	Country	IM	Rank	Country	IM
1	Rwanda	9.59	34	Indonesia	1.57	67	Azerbaijan	-1.91
2	Botswana	7.20	35	Iran	1.51	68	Costa Rica	-1.91
3	Gabon	6.22	36	Gambia, The	1.45	69	Jamaica	-2.24
4	Liberia	6.15	37	PN Guinea	1.40	70	Fiji	-2.32
5	Namibia	5.82	38	Peru	1.33	71	Dom. Rep.	-2.38
6	Niger	5.48	39	Colombia	1.04	72	Mauritius	-2.45
7	Madagascar	5.11	40	Paraguay	1.00	73	Sudan	-2.52
8	South Africa	5.09	41	Belize	0.97	74	Panama	-2.55
9	Nepal	4.98	42	Ukraine	0.95	75	Bulgaria	-2.77
10	Comoros	4.72	43	Morocco	0.85	76	Vietnam	-2.80
11	Djibouti	4.47	44	Philippines	0.79	77	Tunisia	-3.18
12	Guatemala	3.94	45	Lao PDR	0.74	78	Cameroon	-3.25
13	Guinea	3.71	46	Egypt	0.53	79	Guyana	-3.49
14	Tajikistan	3.41	47	Honduras	0.38	80	Lesotho	-3.51
15	Nicaragua	3.35	48	Burundi	0.23	81	Burkina Faso	-3.52
16	Turkey	3.33	49	Russian Fed.	0.23	82	Mauritania	-3.77
17	Mozambique	3.15	50	Angola	0.23	83	Lebanon	-3.83
18	Bhutan	3.02	51	Lithuania	0.10	84	Kyrgyz Rep.	-3.90
19	Sierra Leone	2.82	52	Tanzania	-0.07	85	Uganda	-4.14
20	Brazil	2.79	53	Romania	-0.19	86	Kazakhstan	-4.38
21	Bangladesh	2.70	54	El Salvador	-0.28	87	Cen. Afr Rep.	-4.56
22	Benin	2.36	55	Mongolia	-0.39	88	India	-4.57
23	Swaziland	2.31	56	Pakistan	-0.69	89	Sri Lanka	-4.60
24	Guinea-Bissau	2.30	57	Nigeria	-0.94	90	Uzbekistan	-4.85
25	Moldova	2.26	58	Armenia	-0.95	91	Zambia	-5.89
26	Algeria	2.24	59	Uruguay	-1.21	92	Belarus	-6.24
27	Togo	2.19	60	Chile	-1.23	93	Thailand	-6.61
28	Ecuador	2.08	61	Cote d'Ivoire	-1.26	94	Kenya	-6.62
29	Mexico	2.00	62	Argentina	-1.38	95	Ghana	-7.40
30	Malawi	2.00	63	Senegal	-1.42	96	Chad	-7.90
31	Latvia	1.88	64	Suriname	-1.48	97	Congo, Rep.	-9.62
32	Bolivia	1.63	65	Malaysia	-1.66	98	China	-11.01
33	Georgia	1.62	66	Mali	-1.67			

IM: improvement metric (change in distance to frontier between 1990 and 2009); higher rank and lower IM scores indicate worse performance.

Table 5: Switch by Improvement Metric, 1990-2009

NEGATIVE SWITCH		POSITIVE SWITCH	
Country	IM	Country	IM
Ghana	-7.40	Botswana	7.20
Kenya	-6.62	Namibia	5.82
Thailand	-6.61	Madagascar	5.11
Belarus	-6.24	Guatemala	3.94
Zambia	-5.89	Guinea	3.71
India	-4.57	Benin	2.36
Uganda	-4.14	Swaziland	2.31
Lebanon	-3.83	Algeria	2.24
Bulgaria	-2.77	Mexico	2.00
Mauritius	-2.45	Ukraine	0.95
Malaysia	-1.66	Burundi	0.23
Suriname	-1.48		
Cote d'Ivoire	-1.26		

IM: improvement metric (change in distance to frontier between 1990 and 2009); higher rank and lower IM scores indicate worse performance.