Session Number: Session 6A
Time: Thursday, August 28, PM

Paper Prepared for the 30th General Conference of
The International Association for Research in Income and Wealth

Portoroz, Slovenia, August 24-30, 2008

Measuring Health Inequality with Realization of Conditional Potential Life Years (RCPLY): Estimated using Frontier Methods

Dennis Petrie (University of Dundee)
Kam Ki Tang (University of Queensland)
D. S. Prasada Rao (University of Queensland)

For additional information please contact:

Name: KK Tang
Affiliation: University of Queensland
Full mailing address: School of Economics, University of Queensland, QLD 4072, Australia
Email address: kk.tang@uq.edu.au

Measuring Health Inequality with Realization of Conditional Potential Life Years (RCPLY): Estimated using Frontier Methods

Dennis Petrie[a], Kam Ki Tang[*, b], D. S. Prasada Rao[b]

Paper prepared for IARIW 30th General Conference
Slovenia, August 24-30, 2008

Abstract

In a series of papers (Tang, Chin and Rao, 2008; and Tang, Petrie and Rao 2006 & 2007), we have tried to improve on a mortality-based health status indicator, namely age-at-death, and its associated health inequality indicators that measure the distribution of age-at-death. The main contribution of these papers is to propose a frontier method to separate avoidable and unavoidable mortality risks. This has facilitated the development of a new indicator of health status, namely the Realization of Potential Life Years (RePLY). The RePLY measure is based on the concept of a "frontier country" that, by construction, has the lowest mortality risks for each age/sex group amongst all countries. The mortality rates of the frontier country are used as a proxy for the unavoidable mortality rates, and the residual between the observed mortality rates and the unavoidable mortality rates are considered as avoidable morality rates. In this approach, however, countries at different levels of development are benchmarked against the same frontier country without considering their heterogeneity. The main objective of the current paper is to control for national resources in estimating (conditional) unavoidable and avoidable mortality risks for individual countries. This allows us to construct a new indicator of health status – Realization of Conditional Potential Life Years (RCPLY). Furthermore, in the previous papers, we construct the frontier using a data envelopment method without controlling for noise in the data. The second objective of the paper is to use Stochastic Frontier Analysis (SFA) methods to improve on the frontier estimation. The paper presents empirical results from a dataset of life tables for 167 countries from the year 2000, compiled and updated by the World Health Organization. Measures of national average health status and health inequality based on RePLY and RCPLY are presented and compared.

Keyword: Mortality risk, avoidable deaths, health inequality, data envelopment analysis, stochastic frontier analysis.

JEL Classification: D6, I12

a Economic Studies, University of Dundee, Scotland
b School of Economics, University of Queensland, Australia
* Corresponding author. Address: School of Economics, University of Queensland, QLD 4072, Australia. Telephone: +617 3365 9796. Fax: +617 3365 7299. Email: kk.tang@uq.edu.au.

1. Introduction

Measuring health inequality within a population is more difficult than measuring its average health status. A key reason is the lack of reliable indicators of individual health status. In the case that such indicators do exist, like body mass index and self-reported health status[1], data are typically available only for individual countries at sporadic years. This makes comparisons of health inequalities across countries or over time very difficult. A health status measure that seems to be relatively free from this data problem is age-at-death, i.e. length-of-life. In fact, age-at-death was one of the first indicators to be used to measure health inequality (Le Grand 1987, 1989).

Using age-at-death as an indicator of health status has several merits. Firstly, there is little ambiguity in deciding whether a person is alive or dead. Secondly, other things equal, better health should lead to a higher age-at-death. Thirdly, vital statistics are one of the mostly commonly collected data, even in many poor countries. As a result, age-at-death data are available for many countries as well as over time. The publication of life tables, which standardize mortality statistics, further facilitates cross country and temporal comparisons of health status.

However, age-at-death also has its limitations as a health status indicator. Firstly, it is uninformative about the morbidity of individuals while alive. A person who died at an old age but had suffered from long term illness may arguably be worse off than a person who lived a shorter but otherwise very healthy life. Secondly, and more importantly, age-at-death does not distinguish between avoidable and unavoidable deaths. The very fact that everyone must die at some point of his or her life is the strongest evidence that some mortality risks are unavoidable. To the extent that unavoidable deaths, by definition, cannot be prevented by intervention, they should have relatively smaller immediate policy and resources implications than avoidable deaths. A new indicator that focuses only on the age-at-death of avoidable

[1] For instance, Allison and Foster (2004) use self-reported health status data from the US National Health Interview Survey to examine health inequality in the US.

death (i.e. age-at-avoidable-death) has been recently introduced by Tang, Chin and Rao (TCR) (2008) to address the second issue. Building on that effort, Tang, Petrie and Rao (TPR) (2006; 2007) further integrate the proportions of avoidable and unavoidable deaths and age-at-avoidable-death into a more comprehensive health status indicator called the Realization of Potential Life Years (RePLY).

The RePLY indicator measures the extent to which people have realized their potential life years. For people whose deaths are unavoidable, by definition, their RePLY measure will be equal to one; for people whose deaths are avoidable, their RePLY measure will be equal to their age-at-death as a proportion of their potential age-at-death. The numbers of avoidable and unavoidable deaths are estimated based on the probabilities at which the two types of deaths occur in each age/sex group. For health inequality analysis, RePLY can be used to replace age-at-death to measure health status on an individual basis and, hence, its distribution across the population. The fact that RePLY has filtered out the natural mortality differences between ages and sexes means that it can provide more useful information about whether an intervention for a given age/sex group is likely to be effective in reducing its morality in the short to medium run and, thus, about the cost effectiveness of health resource allocation.

The estimation of potential age-at-death in TPR (2006; 2007) is based on the identification of a “frontier profile” of mortality rates of 191 countries. This leads to the concept of a reference or frontier country[2], whose mortality rates, by assumption, are a proxy for unavoidable morality risks. The gap between the mortality rate of each age/sex group of a country and that of the frontier country is an indication of the country’s excess or avoidable mortality risks for that group. It is postulated that if the country has the same amount of resources as the frontier country and uses it as efficiently, it could close the mortality gap. The use of a large cross-country dataset allows us to compare and contrast the levels of health status and inequality across both developing and developed countries. The drawback of this

[2] In previous studies, we use the term reference country. However, in this paper we use the term frontier country to match the current focus on the estimation of the frontier mortality rates.

approach is that the frontier profile of mortality rates are, as expected, determined by the mortality rates of mostly high income countries. This means that the health performance of low income countries is benchmarked against that of their affluent counterparts. However, it is unrealistic to expect that the government of poorer countries could provide the same level of health care services to their people as in rich countries. To the extent that income is likely to be a crucial determinant of mortality rates, the avoidable mortality gap currently identified in the RePLY framework does not indicate how much improvement these poor countries, themselves, could possibly achieve in the short run through better usage or allocation of the resources at their disposal. In a sense, the RePLY framework measures health inequality from a global perspective and what the global community could achieve by a reallocation of resources within as well as across countries. In summary, if our interest is on global health inequality, RePLY based measures will be useful; on the other hand, if our interest is on health inequality within countries, then we should benchmark the health performance of an individual country against a reference country that has comparable resources at its disposal. The main focus of this paper is on the second case, that is, to develop a health status indicator that takes into account of the short term resource constraints faced by countries, and use it to measure health inequality within countries.

TPR (2006; 2007) estimate the frontier mortality profile using a data envelopment method. As a non-parametric method, the method does not account for the natural variation of death rates (i.e. noise) for a particular year. The stochastic variation in mortality rates could affect the position of the frontier and thus the accuracy of resulting health status and inequality measures. The second objective of this paper is thereby to control for this natural variation (i.e. noise) in the data in order to obtain a more robust estimation of the mortality profile of the frontier country. To summarize, this paper aims to improve on the estimation of the frontier mortality profile by taking into account the short-term resource constraint for an individual country and minimise the effect of the data noise on the indicator. To achieve these objectives, we modify the RePLY measure in the following two, progressive, steps.

Firstly, we estimate the frontier mortality profile using the Data Envelopment Analysis (DEA) method controlling for the resources available to each country in the short run. This allows us to construct a new measure of health status – Realization of Conditional Potential Life Years (RCPLY). Using this new health status indicator, we construct health inequality indicators in the same way as the indicators based on age-at-death or RePLY. Secondly, we estimate the frontier mortality profile using Stochastic Frontier Analysis (SFA) methods to control for the noise in the data. This leads to a different set of estimates of RCPLY and associated health inequality indicators.

Including the original RePLY measure, we will estimate in total three health status measures, namely RePLY-DEA, RCPLY-DEA, and RCPLY-SFA.[3] A comparative analysis of the findings from the three measures can be used in gauging the importance of controlling for resources and the natural data variation. Furthermore, the use of RCPLY can open a new dimension of assessing the performance of health systems that is not possible with RePLY. This is because, as explained in section 3, RCPLY has embodied a measure of technical efficiency of the health systems; as a result, comparison of RCPLY across countries is essentially a comparison of the efficiency of their health systems.

The rest of the paper is organized as follows. Section 2 explains the concepts of unavoidable mortality risk and RePLY. Section 3 explains the concept of RCPLY and how it can be constructed using DEA methods. Section 4 extends the methodology discussion to using SFA methods to estimate RCPLY. We relegate some technical details of the actual estimation procedures to Appendix 1. Section 5 explains the data used in the empirical work. Section 6 reports and discusses the empirical findings. The last section offers some concluding remarks.

[3] We have also estimated RePLY-SFA. However, since the main contribution of the paper is to develop the new indicator RCPLY, not to contrast the DEA and SFA methods, we omit it in the current paper.

2. Unavoidable Mortality Risks and Realization of Potential Life Years (RePLY)

2.1 Reference Distribution of Unavoidable Mortality Risks

Mortality risks are not static; they can be affected by genes, resources, technology, and environment. The effects of these four factors are not independent of each other. For instance, the fact that mortality rate is strongly age and sex dependent is an evidence of the effects of genes; however, technology, such as in vaccination and medication, can mitigate those effects to various degrees. Resources on education, shelter, law and order etc. can also reduce mortality risks. Furthermore, while exposure to different types of environmental factors, such as cold weather and heat wave, could lead to very different mortality risks, people could be shielded from those environment risks when sufficient resources are in place (TPR, 2008; TCR, 2008). In other words, ultimately the determination of mortality risks comes down to just three aspects: genetic factors, resources, and technology.

For a given level of technology, no matter how many resources available, some mortality risks, like those related to genes and chance, cannot be eliminated. These mortality risks can be classified as unavoidable mortality risks. The gap between the actual mortality risks and the unavoidable mortality risks equals the avoidable mortality risks. That is, we assume *avoidable and unavoidable mortality risks to be mutually exclusive* (A1). Here we also postulate that unavoidable mortality risks are largely determined by genes and technology, whereas avoidable mortality risks are determined by genes, technology and resources.[4] Furthermore, given genes of different races are almost identical and most non-military technology is globally tradeable, it is reasonable to assume that *unavoidable mortality risks are age and sex specific, time variant (as technology changes), but largely*

[4] Genes and technology matter for both avoidable and unavoidable mortality risks because of the following reasons. Firstly, genes and technology determine the frontier mortality risk, i.e. the unavoidable mortality risk. Secondly, since the avoidable mortality risk is defined here as the residual between the observed mortality risk and the unavoidable mortality risk, it therefore must be affected by the position of the frontier and, thus, genes and technology.

country invariant (A2).[5] On the other hand, we assume *avoidable mortality risks to be not only age and sex specific and time variant, but also country variant* (A3) as countries have different resource accessibilities.

Avoidable mortality is a long-standing notion in the health literature. Yet, how to determine whether a death is avoidable or unavoidable is a contentious issue. For instance, in the calculation of potential years of life lost (PYLL) typically an upper bound of age 70 is used (e.g. Romeder & McWhinnie 1977), implicitly assuming that all deaths before age 70 are avoidable and all deaths at 70 or above are unavoidable, regardless of the cause of deaths. On the contrary, the Center for Disease Control and Prevention of the United States (CDC 1986) classifies deaths caused by violence, starvation, consumption of tobacco, poor diet and physical inactivity (i.e. obesity), alcohol consumption, toxicants, illicit use of drug, and vehicle accidents as preventable. A limitation of this approach is that it identifies only a subset of avoidable deaths and noticeably excludes all disease related deaths.

An alternative approach is to set the actual mortality rates of a group, typically a country or province with a very high life expectancy, as the reference (i.e. unavoidable) rates to measure the excess (i.e. avoidable) mortality of the others. This approach has a long tradition in the literature, starting with Farr (1885), and then being adopted by Woolsey (1981), Uemura (1989), McCracken (2002), and, most recently, by TCR. In Farr and McCracken, regions with the highest socioeconomic status are chosen as the reference group. A shortcoming of this approach is that a single region is unlikely to have the lowest mortality rate for all age groups. Woolsey, Uemura and TCR circumvent this problem by constructing the reference unavoidable morality rates using data from multiple regions or countries. Amongst all these studies, TCR are the only ones that use international mortality data that cover countries of all levels of income and development – 191 countries in total. Using a data envelopment method, TCR construct a hypothetical frontier country that has the lowest

[5] In the context of this paper, the unavoidable mortality risks referred in A2 is the unconditional one. This assumption will need to be modified later on.

mortality rates for each of the age/sex groups. The mortality rates of a frontier country are then used as the unavoidable mortality rates.

The data envelopment method used by TCR is as follows. Suppose there are K countries and the probability of a person in country k who survives to age x will die before reaching the next birthday is denoted by q_{xk}.[6] Let $\tilde{q}_x$ be the probability of dying for a person of the same age in the hypothetical frontier country. Then, $\tilde{q}_x$ is defined as

$$\tilde{q}_x = \begin{cases} \min_k \{q_{xk}; k = 1, 2, ...K\} & x < X \\ 1 & x \geq X \end{cases} \quad (1)$$

The first two columns on the left hand side of Table 1 shows the country that has the lowest mortality risks for each age/sex group using the dataset in this paper and therefore contribute to the construction of the frontier mortality profile. This list is not the same as that in TCR because firstly, the World Health Organization has subsequently updated their dataset to provide more accurate estimates; and secondly, we only consider 167 countries due to the lack of other data (details of the dataset are discussed in section 5). The use of a slightly smaller dataset has negligible effects on the identification of the frontier mortality profile, as reflected in the fact that the list of countries on Table 1 remains dominated by OECD or other high income countries. See TCR for a detailed discussion of the robustness of the frontier mortality profile.

2.2 Realization of Potential Life Years (RePLY)[7]

Tang, Petrie & Rao (2006) employ the measures of avoidable and unavoidable mortality risks derived using the method of TCR to develop a new measure of health status, namely the Realization of Potential Life Years (RePLY). The RePLY for a person is defined as the ratio of his actual length-of-life (i.e. age-at-death) to his potential length-of-life. For an avoidable

[6] It should be noticed that q is a conditional probability as it is conditional on the person having survived from birth till age x. However, we simply use the term “probability” rather than “conditional probability” throughout the paper so that we can preserve the word “conditional” for cases where the probabilities are measured after controlling for income.
[7] This section is drawn from Tang, Petrie & Rao (2006).

death that occurs at age *x*, the person in concern has not fully realized his potential length-of-life. Should the person have had access to the same amount of resources as his peers in the frontier country, he/she would be expected to live till $\tilde{e}_{xs} + x$, where $\tilde{e}_{xs}$ is the life expectancy for an identical person in the frontier country.[8] Therefore, the person has realized his potential life years to a degree equal to the ratio $x/(\tilde{e}_{xs} + x)$. In contrast, for an unavoidable death at any age, the person in concern has already received at least 100 percent of the resources required to live up to his or her potential length-of-life that nature and current technology permit (i.e. additional resources would not have made the person live longer). In summary, the RePLY measure associated with each observed death at age *x* can be expressed as:

$$RePLY_{xs} = \begin{cases} 1 & \textit{for an unavoidable death} \\ \dfrac{x}{\tilde{e}_{xs} + x} & \textit{for an avoidable death} \end{cases} \qquad (2)$$

Since unavoidable mortality risks are assumed to be invariant across countries, the number of unavoidable deaths, U_{xsk}, of the group xsk can be estimated by

$$U_{xsk} = N_{xsk}\, \tilde{q}_{xs} \qquad (3)$$

where N_{xsk} is the size of the group in the stationary population[9].

The number of avoidable deaths for the group, A_{xsk}, is equal to the number of all deaths minus unavoidable deaths:

$$A_{xsk} = D_{xsk} - U_{xsk} = N_{xsk}\, q_{xsk} - N_{xsk}\, \tilde{q}_{xs} = D_{xsk}(1 - \tilde{q}_{xs} / q_{xsk}) \qquad (4)$$

where D_{xsk} is the number of deaths of the group, and $\tilde{q}_{xs} / q_{xsk}$ is the probability that an observed death is unavoidable. Therefore, the closer q_{xsk} is to $\tilde{q}_{xs}$, the larger the proportion of unavoidable deaths and, thus, the smaller the proportion of avoidable deaths.

[8] In life tables, life expectancy at age *x* in country *k*, e_{xk}, is defined as the number of years ahead a person is expected to live if the person has lived to age *x*.

[9] See section 5 for an explanation of why the stationary population is used.

In essence we have divided deaths for each age/sex group into two sub-groups: unavoidable deaths and avoidable deaths, whose achieved health statuses are given a value of unity and a value less than one respectively. Once the health statuses are determined for all sub-groups across all ages, sexes and countries, we can construct various indicators of group or national average health status (e.g. mean) and health inequality indicators (e.g. Gini coefficients). Since the unavoidable mortality risks for each age/sex group are constructed separately, the natural mortality differences between different groups are removed from the resulting health indicators. This makes the health measures for different groups commensurable and greatly facilitates the assessment of health inequalities between ages or sexes. On other hand, due to the fact that life tables only stratify a population by age and sex, RePLY cannot be used to measure inequality across other dimensions, such as income or education.[10] Besides this data-related constraint, RePLY has two other methodology-related limitations. Firstly it is assumed that unavoidable mortality risks are country invariant and secondly the frontier construction can be affected by noise. These are discussed in sequence in the next two sections.

3. Conditional Unavoidable Mortality Risks and Realization of Conditional Potential Life Years (RCPLY)

3.1 GDP per capita as a measure of national resources

The assumption of unavoidable mortality risks being country invariant is based on the assertion that unavoidable mortality risks are driven by, besides genes, globally available technology. A limitation of this assertion in practice is that even though technology is globally available, its purchase and adoption is resource dependent. For instance, poor countries are typically in great need of even basic medical supplies and personnel. Since the reference mortality rates constructed by TCR is constructed using a simple envelopment of all

[10] Though if data on mortality rates for these groups existed, then RePLY could easily be extended to incorporate these dimensions.

the countries without controlling for development levels, they are dominated by countries with high income levels. Even though income is not fixed in the long term, it is of great inertia in the short to medium term. As a result, the estimates of avoidable mortality rates for low income countries, based on the global frontier of unavoidable mortality rates, are only a very long-run concept with little relevance to policy in the short to medium term, unless resources can be redistributed from other countries.

In this paper we propose to measure avoidable mortality risks after controlling for country-specific resources as measured by GDP per capita in the estimation of the frontier mortality profile. Obviously, income is not the only dimension of health-related resources. Other important resources (broadly defined) include education, health expenditure, and natural environment. GDP per capita is the only resource measure used in this paper for a number of reasons. First of all, since we are dealing with national level data, GDP per capita is arguably the most useful single measure of a country's available resources. Secondly, what we want to control for is the total amount of resources available to a nation, not the allocation of resources amongst competing usages. This is because even if nations are constrained by the total amount of resources available to them, they still can manoeuvre the allocation of resources across different health-related sectors, such as health, education, water and sanitation, and housing.

Another possible determinant of health is education. In this regard, it is important to distinguish between education expenditure and education level. The education level of the population, as measured by, for instance, average years of schooling, is a stock measure, while education expenditure is a flow measure. The education level of the population is related to education expenditure in the past and therefore cannot be changed in the short to medium term. Therefore, it could be argued that in principle education level should be included as another resource measure besides GDP per capita. However, in practice education is known to be highly correlated with income. Furthermore, although there are existing data sets on average years of schooling, especially the widely used Barro and Lee (2000) dataset, the limitation of its country coverage means that the inclusion of education would substantially reduce our sample size. Lastly, in the stochastic frontier analysis, we find that the estimates are sensitive to model specifications, and become less stable as more input variables are used (see later sections for more details on this aspect). Therefore, in the current paper we decide not to include education level or education expenditure.

Lastly, countries in different parts of the world are exposed to very different kind of climate and biological environment in general. To the extent that many environmental factors cannot be manipulated in the short run or even in the long run in individual countries, one may argue that those factors should be controlled for in estimating the frontier mortality profile. An issue of controlling for environmental factors is that it is not clear that they have a monotonic relationship with mortality rates. This is problematic in DEA estimation as it requires a prior knowledge on the direction of the contribution of an input factor to output. The SFA method does not require such a prior knowledge but still requires a specified functional form, and again confronts the aforementioned model sensitivity issue. Therefore, we leave the environmental issue for further research.

All in all, based on theoretical and practical considerations, in this paper we use only GDP per capita to indicate the amount of resources available to each country. When the mortality risks of a country is benchmarked against the mortality risks of the best performing countries regardless of their income levels, we will obtain the original RePLY; and when benchmarked against those of similar income levels, we will obtain a new measure – Realization of Condition Potential Life Years (RCPLY).

In developing the concepts of (unconditional) avoidable and unavoidable mortality risks, three assumptions have been made as stated in section 2. These assumptions are expanded to include conditional avoidable and conditional unavoidable mortality risks. The fourth assumption is a straightforward extension of A1: *conditional avoidable and conditional* *unavoidable mortality risks are mutually exclusive* (A4). However, since conditional unavoidable mortality risks are contingent on a country's income, it must be country specific, like conditional avoidable mortality risks. Therefore, the extensions of A2 and A3 can be condensed into a single one: *conditional avoidable and conditional unavoidable mortality risks are age, sex and country specific*[11]*, and time variant (as technology changes)* (A5).

3.2 The general frontier approach to the determination of conditional and unconditional mortality risks

3.2.1 The frontier function

In this section we describe the frontier approach to determine conditional and unconditional mortality risks for different age/sex groups. Consider a person of age *x* and sex *s*. Let the survival probability of the person reaching the next age bracket be p_{xs}, which is equal to one minus the probability of death (i.e. $p_{xs} = 1 - q_{xs}$).

The survival probability is used as the output of the "health production" in order to ensure a monotonically increasing functional relationship with the input measure – GDP per capita (expressed in logarithmic terms). The frontier approach stipulates that, for a given technology level, the survival probability is a function of income, *y*:

$$\tilde{p}_{xs} = f_{xs}(y) \qquad (5)$$

where the function is assumed to be different for each age/sex groups. The function f_{xs} shows the maximum feasible survival probability for a given level of income, where all the observed survival probabilities, p_{xs}, are below or equal to the maximum feasible level of $\tilde{p}_{xs}$. In addition, we allow f_{xs} to exhibit variable returns to scale in the DEA estimation. This is because, although we already use log income as the input, the underlying relationship between

[11] Although we only control for income in the current paper, the concept of conditional avoidable and conditional unavoidable mortality risks is much more general. Therefore, we state A5 in terms of country specificity rather than income specificity.

p and *y* could be more or less convex than what a logarithmic function allows. In fact, in the vast majority of cases, the estimates indicate that it exhibits decreasing returns to scale.

3.2.2 Conditional unavoidable mortality risks

We demonstrate the concepts using Figure 1. This figure is specific to a particular age/sex group. Suppose country *k* has a real per capita income of y_k and let the observed survival probability for country *k* be p_{xsk}. The solid line shows the value of the frontier function f_{xs} at different income levels. Given the frontier function, it is possible to identify the maximum feasible survival probability conditional on the income level y_k:

$$\hat{p}_{xsk} = f_{xs}(y_k) \qquad (6)$$

By definition, we have $p_{xsk} \le \hat{p}_{xsk} \Rightarrow q_{xsk} = 1 - p_{xsk} \ge 1 - \hat{p}_{xsk} = \hat{q}_{xsk}$. Mortality risk $\hat{q}_{xsk}$ is the lowest mortality risk projected from observed countries with income levels around y_k.[12] These mortality risks are defined in this study as the *conditional unavoidable mortality risk or rate*.

The RCPLY measure associated with each observed death at age *x* of sex *s* is expressed as:

$$RCPLY_{xsk} = \begin{cases} 1 & \textit{for a conditional unavoidable death} \\ \dfrac{x}{\hat{e}_{xsk} + x} & \textit{for a conditional avoidable death} \end{cases} \qquad (7)$$

where $\hat{e}_{xsk}$ is the life expectancy of the hypothetical "local frontier country" and is constructed from the series of $\{\hat{q}_{xsk}\}$ using standard life table methods. It should be noticed that there is only one frontier for each age/sex group. The "local frontier country" for a country is hypothetically the best performing country with a similar income level, and the

[12] In the actual estimation, if there is no other country of income level the same as y_k, then $\hat{q}_{xsk}$ is computed as a combination of the lowest mortality rates of the two most nearby countries, one with higher income than country *k* and the other lower.

“global frontier country” is the hypothetically best performing country of all income levels; that is, they locate on different income regions of the *same* frontier rather than on different frontiers. For countries with different income levels, they will have different local frontier countries to benchmark against, but they will still have the same global frontier country.

When benchmarked against the local frontier country, the number of conditional unavoidable deaths, U^{C}_{xsk}, is given by

$$U^{C}_{xsk} = N_{xsk}\,\hat{q}_{xsk} \tag{8}$$

The number of conditional avoidable deaths for the group, A^{C}_{xsk}, is equal to the number of all deaths minus that of conditional unavoidable deaths:

$$A^{C}_{xsk} = D_{xsk} - U^{C}_{xsk} = N_{xsk}\,q_{xsk} - N_{xsk}\,\hat{q}_{xsk} = D_{xsk}(1-\hat{q}_{xsk}/q_{xsk}) \tag{9}$$

3.2.3 Unconditional unavoidable mortality risks

In Figure 1, the maximum achievable survival probability for a given income level y_k is given by $\hat{p}_{xsk}$. However, the maximum achievable survival probability from the frontier function as income increases is given by $\tilde{p}_{xs}$. This means that irrespective of the level of income, for any observed survival probability p_{xsk}, we have $p_{xsk} \le \hat{p}_{xsk} \le \tilde{p}_{xs}$. The corresponding inequalities for the mortality risks are $q_{xsk} \ge \hat{q}_{xsk} \ge \tilde{q}_{xs}$ for all income levels. Since $\tilde{q}_{xs}$ does not depend on any specific income level, these mortality risks are labelled *unconditional unavoidable mortality risks*. The unconditional unavoidable mortality risk, $\tilde{q}_{xs}$, defined here is the same as the *unavoidable mortality risk* concept introduced in TCR and used in TPR; the two studies do not consider conditional unavoidable mortality risk, $\hat{q}_{xsk}$.

Since $\hat{q}_{xsk} \ge \tilde{q}_{xs}$, we have $U^{C}_{xsk} \ge U_{xs}$. That is, the number of conditional unavoidable deaths will be at least as large as the unconditional unavoidable deaths. This is because, when the inequality holds, some of the unconditional unavoidable deaths are due to the fact that country *k* has fewer resources than some other countries. The number of deaths that could be avoided if the country is given sufficient resources is given by

$$U^C_{xsk} - U_{xs} = A_{xs} - A^C_{xsk} = N_{xsk}(\hat{q}_{xsk} - \tilde{q}_{xs}) = D_{xsk}(\hat{q}_{xsk} - \tilde{q}_{xs}) / q_{xsk} \qquad (10)$$

3.2.4 Measures of technical efficiency

Using Figure 1, we can define the level of technical efficiency[13] achieved by a country. The technical efficiency (TE) measure shows the survival probability attained by a country relative to the maximum achievable survival probability at its income level. Thus the TE measure for country *k* with income y_k is given by

$$TE_{xsk} = \frac{p_{xsk}}{\hat{p}_{xsk}} \qquad (11)$$

By definition, we have $0 \le TE_{xsk} \le 1$. The technical efficiency measure can be used as an indicator of efficiency of the health system in a given country. Countries that lie on the frontier are considered as technically fully efficient. An important point in the determination of technical efficiency is that country *k* is benchmarked against and compared with the best performing countries with similar income levels. Thus, improving the TE levels could be considered as an achievable target as set by peer countries with similar levels of income.

It should be noticed that RCPLY thus already embodies this measure of technical efficiency. This is because the closer p_{xsk} to $\hat{p}_{xsk}$ is, the closer A^C_{xsk} to zero is and, thus, the closer $RCPLY_{xsk}$ to one will be. This implies that the efficiency of national health systems will affect the average health status of the population (as reflected in group or national average measures of RCPLY) and its health inequality (as reflected in RCPLY based inequality indicators). The reason why efficiency matters for a nation's average health status is obvious: the more efficient the health system is, the more lives could be saved with the

[13] Here we measure TE using output orientation. See Appendix 1 for further discussion.

same resources. The reason why efficiency also matters for a nation's health inequality, however, needs some explanation. Recall that our notion of health equality is that everyone realizes his or her potential life years to the same degree. For those who died of unavoidable causes, they had all the resources required to live up to their conditional potential or even more; for those who died of avoidable causes, they could have been saved and, thus, realized more of their potential if they were given more resources or if their resources were used more efficiently. So here the health system can affect health inequality through either better allocation of resources amongst those who are in need (i.e. improving allocation efficiency) or better usage of the allocated resources (i.e. improving technical efficiency). For instance, a reallocation of resources from those who died of unavoidable causes to those died of avoidable causes could increase the overall equality, especially if the former has used more resources that what they just needed to live up to their potential. On the other hand, even if there is no reallocation of resources, a more efficient usage of the allocated resources can also affect health inequality. This is because, the more efficient the health system is, the smaller the proportion of conditional avoidable deaths. Since conditional unavoidable deaths and avoidable deaths are of different RCPLY scores, this will lead to change in RCPLY based health inequality measures. However, it should be emphasized that there is no a prior guarantee that higher efficiency will lead to greater health equality. For instance, if there is large improvement in usage efficiency but limited improvement in allocation efficiency, it is possible that the health improvement in some segments of the population will be much larger than that in other segments, resulting in a rise in average health status but deterioration in health equality.

4. Frontier Estimation

The most important step in constructing RCPLY is to identify the frontier. In order to identify the frontier it is necessary to have a cross-country data set for each age/sex group. There are two methods available for this purpose, the data envelopment analysis (DEA) and the stochastic frontier analysis (SFA).

4.1 Estimating the frontier using Data Envelopment Analysis (DEA)

The DEA method constructs a frontier using a piecewise linear frontier similar to the one drawn in Figure 1. Since we have survival probabilities expressed as a function of only one determinant, income, it is possible to construct these frontiers using simple graphical methods.[14] This is illustrated in Figure 2 using the survival probabilities of males aged 75 of 167 countries. This age/sex group is selected because the large variation in its survival probabilities across countries that makes the visual identification of the frontier much easier. The DEA method has identified five countries with full efficiency, Tanzania, Mongolia, Nicaragua, Mexico, and Japan. These countries, by definition, have zero conditional avoidable mortality risks for this particular age/sex group, and all other countries' mortality rates are benchmarked against combinations of their mortality rates. Amongst these five countries, Japan has the highest survival probability; therefore, it is the only country that has zero unconditional avoidable mortality risks for this age/sex group.

Tanzania is a special case and worth mentioning here. It sits on the "edge" of the frontier mainly because it has the lowest income level ($498) amongst all the countries in the dataset.[15] Due to its status of having the lowest income, even if its survival probability drops to very low, it will remain technically fully efficient.[16] In fact, this is the case for all DEA estimations in this paper, making it the only country that has zero conditional avoidable deaths for all age/sex groups and, thus, perfect conditional health equality! Since this is an artifact of the country being the observation of the lowest income in the dataset, we will not

[14] It is necessary to use linear programming methods to identify the frontier and there by calculating technical efficiencies when multiple inputs and/or multile outputs are present. Details of the general DEA methodology can be found in Coelli, Rao, O'Donnell and Battese (2005).
[15] We have also tried to include an artificial observation of zero input and zero output in the dataset. But it does not change the results for Tanzania or others.
[16] It will cease to become a peer country only if we include an artificial observation of zero input and zero output in the dataset while Tanzania's survival probability drops to sufficiently low.

pay much attention to its result in most of the discussion. But we keep it in the estimation, otherwise, the same situation will hold for the country with the second lowest income level.

Applying the same procedure to all other age/sex groups, we can obtain lists of countries (reported in Table 1) that have zero conditional avoidable mortality risks for all the groups. The lists of countries are noticeably lengthy, especially for ages below 30. A long list typically reflects a more continuous convex frontier for the low income countries, indicating that controlling for income is important in considering the efficiency of the health system. The first possible explanation for this result is that income may be more important in determining the mortality rates for the younger age groups than for the older one. The second explanation, but related to the first one, is that as the size of the population typically gets smaller at high ages, the natural variation (noise) in mortality rates becomes relatively more important as compared to income in driving the observed mortality rates of the high age groups.

Amongst the low income countries, besides the special case of Tanzania, Armenia, Mongolia, Tajikistan, Vietnam, and Yemen are the "regular features" of table, indicating the high relative effectiveness of their health systems given the available resources. The effectiveness of these countries' health systems may be due to the fact that they allocate proportionally more of their national resources to health and/or they use their health-related resources more effectively. In order to identify the relative importance of these two factors, we need to control for the amount of national resources being spent on health. We leave this issue to further research.

4.2 Estimating the frontier using Stochastic Frontier Analysis

As a non-parametric method, DEA has a limitation of not controlling for noise in the data. This is exacerbated by the fact that only 40 out of the 191 countries in the dataset used by TCR have reasonably complete vital statistics, and the mortality data for the rest of the countries are based on estimations from available data. Although TCR has conducted a number of sensitivity tests to ensure the frontier profile of unavoidable mortality risks is robust to outliers, the accuracy of the frontier estimation could be further strengthened by using Stochastic Frontier Analysis (SFA) methods.

When we control for GDP per capita, a linear probability stochastic frontier model for p_{xsk} is

$$p_{xsk} = \beta_{1xs} + \beta_{2xs} \ln(income_k) + v_k - u_k ; e_k = v_k - u_k ; 1 \geq \beta_{1xs} \geq 0,\ \beta_{2xs} \geq 0 \qquad (12)$$

where $\beta_{1xs} \in [0,1]$ is an age/sex specific constant term, $v_k = N(0, \sigma_v^2)$ is a normally distributed error term, $u_k = \left| N(0, \sigma_u^2) \right|$ is a half-normally distributed error term, and it is assumed that $\text{cov}(v_k, u_k) = 0$, and e_k is the total error.

Here v_k is supposed to capture the random measurement errors and/or stochastic variations of the survival probability, and u_k captures the inefficiency of the health system. Due to the existence of the stochastic term v_k, the predicted conditional unavoidable mortality rate, i.e. the mortality rate of the local frontier country, is defined as[17]

$$\hat{q}_{xsk} = 1 - \hat{\beta}_{1xs} - \hat{\beta}_{2xsk} \ln(income_k) \qquad (13)$$

A potential problem of (13) is that, the predicted value of the local frontier country's mortality rate, $\hat{q}_{xsk}$, may lie outside [0, 1]. This problem is more likely to arise when the income level gets closer to the higher end of the income spectrum and the observed survival probability also gets closer to its upper bound. Non-linear models can be utilised to prevent such a scenario. In this paper, we adopt a logit model specification:

$$\ln\left(\frac{p_{xsk}}{1 - p_{xsk}} \right) = \beta_{1xs} + \beta_{2xs} \ln(income_k) + v_k - u_k \qquad (14)$$

The mortality rate of the local frontier country is now given by

[17] The cap above β is to indicate that it is an estimated value. It should not be confused with the cap above *p* or *q*, which is to indicate conditional survival probability or conditional mortality risks.

$$\hat{q}_{xsk} = \left[1 + \exp\left(\hat{\beta}_{1xs} + \hat{\beta}_{2xsk}\ln(income_k)\right)\right]^{-1}, \tag{15}$$

while that of the global frontier country is given by

$$\tilde{q}_{xs} = \min_{y}\{\hat{q}_{xsk}\} \tag{16}$$

Once we have obtained $\hat{q}_{xsk}$, the rest of the procedure is quite similar to that under DEA. In particular, we can compute $\hat{e}_{xsk}$ and thus $RCPLY_{xsk}$ following (7), and the number of unavoidable deaths following (8). On the contrary to the DEA method, since v_k could be positive, for countries that are very close to the frontier, it is possible that $q_{xsk} < \hat{q}_{xsk}$ and thus $A^C_{xsk} < 0$ if we use (9). Since this “out-performance” is assumed to be due to stochastic errors, we can resolve this problem by setting

$$A^C_{xsk} = \begin{cases} D_{xsk}(1 - \hat{q}_{xsk} / q_{xsk}) & \hat{q}_{xsk} \le q_{xsk} \\ 0 & \hat{q}_{xsk} > q_{xsk} \end{cases} \tag{17}$$

5. Data

The proposed method is applied to year 2000 life tables of 191 countries, compiled and recently updated by the World Health Organization in 2002. However, the limitation of GDP per capita data restricts our analysis to 167 countries only. Almost all 24 countries being excluded are small countries, including a number of countries that have very low mortality rates like Monaco, San Marino, Andorra, and Brunei. These countries were prominent in the identification of the global frontier of mortality profile in the studies by TCR and TPR. The removal of these countries will therefore remove some of the concerns that the small size of these countries leads to bias in the estimation of the frontier mortality rates.

Life tables provide information on the estimated probability of death in each age/sex group and subsequently the number of deaths for a stationary population. The stationary population of a country is constructed by repeatedly subjecting the population to the same age/sex specific mortality rate profiles as observed in the year of survey until the demographic structure becomes static. At the same time, the number of births is standardized. Since the number of deaths for each age/sex group in the stationary population remains unchanged over time, they provide the expected number of deaths in each age group associated with a population cohort. As a result, the calculation in this study is based on the stationary population rather than the actual population.[18]

Data on real GDP per capita (PPP, international dollars) is drawn from the World Development Indicators database. We use the average of 1990 to 1999 data to smooth short term fluctuations as well as to mitigate possible reverse causality from health to income.

6. Empirical Results

6.1 Results from Data Envelopment Analysis

Recall that in total we have proposed three health status measures: RePLY-DEA, RCPLY-DEA, and RCPLY-SFA. Based on each of these measures, we can construct various group and national average health status and health inequality indicators. In order to keep the discussion focused, we only report the results of one national average health status indicator and one health inequality indicator: respectively the mean and the Gini coefficient of the corresponding health status measures across all age/sex groups.

The summary statistics of the indicators are reported in Table 2 and the full results can be founded in Appendix 2. Except for income, the statistics are calculated based on the results of 166 out of the 167 countries used in the estimation; the results for Tanzania are not included due to the issue related to its lowest income status as discussed before.

It can be seen from Table 2 that there are huge differences in income across the 167 countries, with the richest (Luxembourg) being almost eight times that of the poorest

[18] The actual population is useful to scale up the absolute size of the stationary population if one is interested in measuring the average health status or health inequality for a multi-country region or the world as a whole.

(Tanzania). On average, a country's own average RCPLY-DEA is about 10 percent[19] bigger than that its average RePLY-DEA. Across countries, the standard deviation of average RCPLY-DEA is about 30 percent[20] smaller than that of average RePLY-DEA. The change in health inequality indicators is even bigger. On average, a country's own RCPLY-DEA Gini coefficient is about 30 percent[21] smaller than its RePLY-DEA Gini coefficient, and the standard deviation across countries is also 27 percent smaller. That is, national average health status and within-country health inequality respectively become much more comparable in values across countries when their income differences are taken into account.

Figure 3 shows a scatter plot of national average RCPLY-DEA against national average RePLY-DEA for the 166 countries (i.e. Tanzania is not included in the figure). All observations lie above the 45 degree line, indicating that the conditional measures of health status will be at least as high as the unconditional ones. This is because an unconditional avoidable death is constructed when countries are benchmarked against the global frontier of unavoidable mortality risks, while a conditional avoidable death is constructed when a country is benchmarked against the local frontier country's mortality risks, which must be equal to or higher than the global frontier country's mortality risks by definition. Therefore, for any country, the number of conditional unavoidable deaths must be equal to or larger than that of unconditional unavoidable deaths, implying that a non-negative number of people will see their health status measures change from less than unity to unity under the RCPLY-DEA indicator compared to under the RePLY-DEA indicator. Furthermore, those who did not receive a health status of unity will still see their health status measure increase under the new conditional indicator. Therefore, no group will register a lower health status when the indicator is shifted from RePLY-DEA to RCPLY-DEA, but some groups will register a higher health status as a consequence, raising the overall health status of the nation.

---

[19] It is based on the mean figure in column (2)/(1).
[20] It is based on the ratio of the standard deviations of (2) and (1), not the standard deviation of (2)/(1).
[21] Again, it is based on the mean figure in column (5)/(4).

As expected, in general average RePLY-DEA is positively related to income level. Therefore, countries at the high end of the average RePLY-DEA spectrum are mostly OECD countries and those at the low end are mostly Sub-Sahara African countries. For countries with average RePLY-DEA close to one, the differences between the two measures are relatively small. However, the difference between the two measures, in general widens as average RePLY-DEA falls. In percentage terms, the change for Malawi is the biggest,[22] with its average RCPLY-DEA 74% higher than its average RePLY-DEA, followed by Sierra Leone which is 62% higher. The difference essentially reflects the gap between the mortality risks of the local and the global frontier countries.

Figure 4 shows a scatter plot of the Gini coefficients of RePLY-DEA and RCPLY-DEA. It looks somewhat like a mirror image of Figure 3. All the RCPLY-DEA Gini coefficients are smaller than their RePLY-DEA counterparts, indicating that the conditional health inequality measures are smaller than the unconditional ones. Again when the RePLY-DEA Gini coefficients are close to zero (i.e. perfect equality), controlling for income makes little difference to the resulting RCPLY-DEA Gini coefficients. However, as health inequality increases, the difference between the two indicators becomes wider. The explanation for this is essentially the same as that for Figure 3 and as follows.

In general, the RePLY-DEA Gini coefficient is negatively related to income. Since the rich countries' mortality risks profiles are very close to that of the global frontier country, most of their deaths are classified unavoidable deaths and have a health status measure equal to unity for RePLY-DEA. As a result, health inequality in these countries is very small despite there being inequalities in age-at-death. For the poor countries, a larger proportion of deaths are classified as avoidable deaths, and avoidable deaths of different age/sex groups are of different health statuses as measured by RePLY-DEA. As a result, health inequality in the poor countries tends to be bigger relative to their more affluent counterparts.

[22] The percentage change of Malawi is even bigger than the 1.72 of Tanzania, though Malawi is also a poor country.

When RCPLY-DEA is used instead to measure health status, it not only increases the number of conditional unavoidable deaths, but also decreases the potential life expectancy of those who died from conditional avoidable deaths, resulting in a larger RCPLY-DEA measure for these individuals. These lead to a reduction of the overall inequality as measured by the Gini coefficient. As shown in Figure 3 that the impact on the measured health status is larger for the low income countries when resources are controlled for, therefore, correspondingly the impact on the measured health inequality is also larger for this group of countries.

6.3 Comparison across Data Envelopment and Stochastic Frontier Analyses

In this section, we compare the results of RCPLY-SFA and RCPLY-DEA. Table 2 shows that, on average, a country's own average RCPLY-SFA is about 5 percent higher than that its average RCPLY-DEA. Across countries, the standard derivation of RCPLY-SFA is 5 percent lower than that of RCPLY-DEA. For health inequality, on average, a country's RCPLY-SFA Gini coefficient is over 40 percent lower than its RCPLY-DEA Gini coefficient, and the standard deviation is also 5 percent lower. These changes in national average health status and health inequality are observed across the board, as reflected in Figures 5 and 6.

Figure 5 is a scatter plot of national average RCPLY-SFA against RCPLY-DEA, and Figure 6 is that of their Gini coefficients. It can be seen that, with the exception of Tanzania and Malawi, all average RCPLY-SFA figures are systematically lower than the corresponding average RCPLY-DEA figures and all RCPLY-SFA Gini coefficient figures are higher than the corresponding RCPLY-DEA Gini coefficient figures. This is because controlling for noise in SFA in general will lower the global and local frontier mortality risks for all age/sex groups and that will raise the RCPLY-SFA measure above the RCPLY-DEA measure for most countries. As most age/sex groups of a country will get closer to the unity health outcome, it lowers the RCPLY-SFA Gini coefficient compared to RCPLY-DEA Gini coefficient (even though it is not necessary at a prior). The exception of Tanzania and Malawi is likely due to the fact that these countries have very low incomes and therefore forces the DEA frontier around it to have a very different shape from the SFA frontier (which takes a particular functional form).

The results in Table 2 also show that the differences of using DEA and SFA to measure average health status and health inequality, while discernable, are not as substantial as the differences between using RePLY and RCPLY. This implies that, controlling for resources constraint, at least quantitatively, is more important than controlling for stochastic variation in the current dataset.

To further illustrate the effects of controlling for income and noise in the data, we list the top and bottom 10 performers in terms of average health status and health inequality in Table 3. The first outstanding feature of the table is that countries that perform well in terms of average health also do so in terms of health equality under each of the three health status indicators, and similarly for those performing poorly. This is illustrated even more clearly in Figures 7 to 9, which plot respectively the Gini coefficients of the three indicators against their own national average. It can be seen that the two measures are highly correlated, with most of the dispersion present in the poorest performing countries. This strong result suggests that, once the natural mortality differences between all age/sex groups are removed from the health status indicator, there is a strong correlation between national average health status and within-country health inequality. However, it should be noticed that because of the data constraint of life tables, we can only measure the health inequalities between different age/sex groups plus the inequalities between the avoidable and the unavoidable deaths within each group, but not that amongst the unavoidable deaths within each group. This means that, further refinement of health inequality measures should focus on within age/sex group inequalities.

The second feature of Table 3 is that the ranking of the countries have changed substantially across the three measures of health status. Since average health and health inequalities are highly correlated, the average and inequality measures give the same picture.

Based on RePLY-DEA, all the top 10 performers are high income, OECD countries. However, when switching to RCPLY-DEA, two low income countries, Yemen and Vietnam, and an upper-middle income country, Costa Rica, make it into the top 10 list. In particular, Yemen and Vietnam achieve an average RCPLY-DEA close to 1 (also see Figure 3). When further moving to RCPLY-SFA, three more middle income countries, Jamaica, Syrian, and Chile also make it to the top 10. These, indicate that these countries are very effective amongst all other countries in their income groups in terms of producing the best mortality outcomes.

On the contrary, changes in the bottom 10 countries are much smaller across different indicators. In particular, across different indicators, the list bottom 10 remains dominated by more or less the same group of Sub-Sahara African countries.

7. Concluding Remarks

The current paper represents another stage in our efforts to improve on health status and associated health inequality indicators. These efforts started with an attempt to improve on the "classic" indicator, age-at-death, which resulted in the development of age-at-avoidable-death (TCR). The methodology of TCR was subsequently used in developing a new indicator, RePLY. The current paper proposes an improved measure, namely RCPLY. At each stage of this evolutionary process, additional factors are controlled for. From age-at-death to age-at-avoidable-death, we have controlled for the differences between avoidable and unavoidable deaths by omitting unavoidable deaths all together; from age-at-avoidable-death to RePLY, we have controlled for the differences between avoidable and unavoidable deaths without omitting the latter; from RePLY-DEA to RCPLY-DEA, we have controlled for the differences in resources across countries; and finally from RCPLY-DEA to RCPLY-SFA to control for stochastic variation in the measured mortality rate. An important merit of the RCPLY measures, either DEA or SFA based, is that they provide a method to integrate multiple key economic and health concepts together into a single framework; those concepts include resources (income), efficiency, health status, health inequality, avoidable and unavoidable deaths.

In a recent review of efficiency analyses of OECD health care sectors, Häkkinen and Joumard (2007) point out that, at the system (i.e. aggregate) level, avoidable deaths is a more relevant health status measure than life expectancy, but there is no agreed framework for applying this concept. Both the RePLY and RCPLY frameworks may provide a possible solution to this problem. On the other hand, although RCPLY has controlled for an additional factor, income, it does not immediately imply that it is definitely preferred to RePLY. Which indicator should be used depends on the task on hand. For instance, if the objective is to examine how within-country health inequality varies across countries, then controlling for country resources will make the comparison more meaningful and, thus, RCPLY should be used. On the other hand, if the objective is to estimate world-wide health inequality, then a global standard in measuring health status will be essential and hence RePLY should be used instead. In other words, RCPLY is more useful for estimating health inequality within countries, while RePLY is more useful for estimating health inequality across countries.

Reference

Allison, RA & Foster, J 2004 'Measuring health inequality using qualitative data' *Journal of Health Economics*, vol 23, no. 3, pp. 505-524.

Barro, RJ. & Lee, J-W 2001 'International Data On Educational Attainment: Updates And Implications,' *Oxford Economic Papers*, vol 53, no. 3, pp. 541-563

Coelli, T, Rao, DSP, O'Donnell, CJ, Battese, GE 2005 An Introduction to Efficiency and Productivity Analysis, 2nd edn., Springer, New York.

Cutler, D, Deaton, A, and Lleras-Muney, A 2006 'The determinants of mortality' *Journal of Economic Perspective*, vol 20, no. 3, pp. 97-120.

Farr, W 1885, Methods for comparing local with standard death-rates, Office of the Sanitary Institute, London.

Häkkinen, U, Joumard I (2007) "Cross-country analysis of efficiency in OECD health care sectors: options for research" OECD Economics Department Working Papers, No. 554.

Le Grand, J 1987. 'Inequality in health: some international comparisons', *European Economic Review* 31: 182-191.

Le Grand, J 1989. 'An international comparison of distributions of ages-at-death', in Health Inequalities in European Countries, J. Fox, Editor. Gower: Aldershort. pp. 75-91.

Maddala, G S 1983. Limited-dependent and qualitative variables in econometrics, Cambridge: Cambridge University Press.

McCracken, K 2002, 'What if New South Wales was more equal?' *NSW Public Health Bulletin*, vol. 13, no. 6, pp. 123-7.

Romeder, J-M & McWhinnie, JR 1977 'Potential years of life lost between ages 1 and 70: An indicator of premature mortality for health planning' *International Journal of Epidemiology*, vol. 8, no. 2, pp. 143-151.

Tang, KK, Chin, JTC & Rao, DSP 2008, 'Avoidable mortality risks and measurement of wellbeing and inequality', *Journal of Health Economics*, vol 27, no. 3, pp. 624-641.

Tang, KK, Petrie, D & Rao, DSP 2006, 'Measuring Health Inequality with Realization of Potential Life Years', paper presented to the WIDER Conference on Advancing Health Equity, 29-30 September, Helsinki.

Tang, KK, Petrie, D & Rao, DSP 2007, 'Measuring health inequalities between genders and age groups with Realization of Potential Life Years (RePLY)', Bulletin of the World Health Organization, vol 85, no. 9, pp. 681-688.

Tang, KK, Petrie, D & Rao, DSP 2008, 'The climate trap of health development: An empirical analysis of the effects of climate and income on mortality' MRG@UQ Discussion Paper, University of Queensland.

Uemura, K 1989, 'Excess mortality ratio with reference to the lowest age/sex-specific death rates amongst countries', *World Health Statistics Quarterly*, vol. 42, pp. 26-41.

Woolsey, TD 1981, *Toward an index of preventable mortality*, 85, Department of Health and Human Services, Hyattsville.

Table 1 Countries with the lowest mortality risks with and without controlling for income

	Countries of the lowest mortality risks without controlling for income		Countries of the lowest mortality risks after controlling for income	
age	**Male**	**Female**	**Male**	**Female**
0	Singapore	Iceland	Belarus, Croatia, Czech Republic, Iceland, Jamaica, Japan, Moldova, Singapore, Slovenia, Tanzania, Viet Nam, Yemen	Belarus, Czech Republic, Iceland, Moldova, Singapore, Slovenia, Tanzania, Vietnam
1	Sweden	Sweden	Austria, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Dominica, Finland, France, Georgia, Greece, Iceland, Ireland, Italy, Luxembourg, Poland, Moldova, Singapore, Spain, Sweden, TFYR Macedonia, Tanzania, Viet Nam, Yemen	Armenia, Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Georgia, Germany, Greece, Italy, Malta, Norway, Poland, Moldova, Seychelles, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, Tanzania, Viet Nam, Yemen
5	Singapore	Slovenia	Armenia, Australia, Austria, Belarus, Belgium, Canada, Chile, Costa Rica, Croatia, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland, Singapore, Slovakia, Slovenia, Sweden, Switzerland, Tajikistan, UK, Tanzania, Yemen	Australia, Austria, Belarus, Belgium, Canada, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Israel, Italy, Japan, Kyrgyzstan, Lithuania, Luxembourg, Malta, Mauritius, Netherlands, New Zealand, Norway, Poland, Moldova, Slovenia, Spain, Sweden, Switzerland, Tajikistan, TFYR Macedonia, UK, Tanzania, Uruguay, Uzbekistan, Yemen
10	Iceland	Luxembourg	Armenia, Australia, Belarus, Bulgaria, Chile, Costa Rica, Croatia, Cyprus, Czech Republic, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Israel, Jamaica, Japan, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Moldova, Saint Vincent and Grenadines, Spain, Sweden, Tajikistan, FYR Macedonia, Tanzania, Uruguay, Uzbekistan, Viet Nam, Yemen	Armenia, Australia, Austria, Belgium, Bulgaria, Canada, Chile, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Kyrgyzstan, Lithuania, Luxembourg, Mongolia, Netherlands, Norway, Poland, Portugal, Republic of Korea, Moldova, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, Tajikistan, TFYR Macedonia, UK, Tanzania, USA, Uruguay, Uzbekistan, Yemen
15	Singapore	Luxembourg	Armenia, Georgia, Madagascar, Mali, Malta, Mozambique, Niger, Moldova, Singapore, Tanzania, Uzbekistan, Yemen	Armenia, Croatia, France, Greece, Hungary, Israel, Italy, Japan, Luxembourg, Mongolia, Netherlands, Poland, Singapore, Slovenia, Spain, Sweden, Switzerland, Tanzania, Yemen
20	United Arab Emirates	Malta	Armenia, Malta, United Arab Emirates, Tanzania, Yemen	Armenia, Canada, Croatia, Denmark, Dominica, Germany, Greece, Ireland, Israel, Italy, Japan, Kuwait, Luxembourg, Malta, Mongolia, Netherlands, Poland, Moldova, Singapore, Slovakia, Spain, Sweden, Tanzania, Yemen
25	Singapore	Malta	Armenia, Japan, Kuwait, Netherlands, Singapore, United Arab Emirates, Tanzania, Viet Nam, Yemen	Armenia, Croatia, Hungary, Iceland, Ireland, Malta, Poland, Singapore, Slovenia, Sweden, Tajikistan, TFYR Macedonia, Tanzania, Viet Nam, Yemen
30	Malta	Sweden	China, Kuwait, Malta, Tanzania, Viet Nam, Yemen	Armenia, Croatia, Malta, Mongolia, Slovakia, Sweden, Tanzania, Viet Nam, Yemen
35	Kuwait	Iceland	China, Kuwait, Malta, Tanzania, Viet Nam, Yemen	Armenia, Chile, Croatia, Georgia, Iceland, Malta, Tanzania, Uzbekistan, Viet Nam, Yemen
40	Iceland	Malta	China, Iceland, Malta, Tanzania, Viet Nam, Yemen	Armenia, Cyprus, Iceland, Israel, Malta, Tanzania, Viet Nam, Yemen
45	Iceland	Kuwait	Albania, China, Iceland, Kuwait, Tanzania, Viet Nam, Yemen	Armenia, Greece, Japan, Kuwait, Malta, Panama, Switzerland, Tanzania, Viet Nam, Yemen
50	Iceland	Spain	China, Costa Rica, Iceland, Kuwait, Malta, Panama, Tanzania, Viet Nam, Yemen	Albania, Armenia, Bahrain, Georgia, Greece, Iceland, Japan, Malta, Panama, Spain, Tanzania, Viet Nam, Yemen
55	Australia	Cyprus	Australia, Mongolia, Panama, Sweden, Tanzania, Viet Nam, Yemen	Albania, Cyprus, Mongolia, Spain, Tanzania, Viet Nam, Yemen
60	Iceland	Japan	Iceland, Nicaragua, Panama, Tanzania, Viet Nam, Yemen	Greece, Japan, Panama, Spain, Tanzania, Viet Nam, Yemen
65	Iceland	Japan	Dominica, Iceland, Tanzania, Yemen	Japan, Panama, Spain, Tanzania, Viet Nam
70	Japan	Japan	Japan, Panama, Tanzania, Yemen	Japan, Panama, Tajikistan, Tanzania
75	Japan	Japan	Japan, Mexico, Mongolia, Nicaragua, Tanzania	Japan, Panama, Tajikistan, Tanzania
80	Mexico	Japan	Mexico, Mongolia, Tanzania	Japan, Tajikistan, Tanzania
85	Mexico	Japan	Mexico, Mongolia, Tanzania	Japan, Tajikistan, Tanzania
90	Malaysia	Japan	Malaysia, Mongolia, Tanzania	Japan, Seychelles, Tajikistan, Tanzania
95	Malaysia	Malaysia	Malaysia, Mongolia, Tanzania	Malaysia, Tajikistan, Tanzania

Table 2 Summary statistics of income, national average health status and health inequality measures

	GDP per capita (1990-99 average)	Average RePLY-DEA	Average RCPLY-DEA	Average RCPLY-SFA (logit, lnGDP)	RePLY-DEA Gini Coeff.	RCPLY-DEA Gini Coeff.	RCPLY-SFA (logit, lnGDP) Gini Coeff.	Average RePLY-DEA/average RCPLY-DEA	Average RCPLY-SFA/average RCPLY-DEA	RCPLY-DEA Gini coeff./RePLY-DEA Gini coeff.	RCPLY-SFA Gini coeff./RCPLY-DEA Gini coeff.
		(1)	(2)	(3)	(4)	(5)	(6)	(2)/(1)	(3)/(2)	(5)/(4)	(6)/(5)
Mean	7494	0.803	0.875	0.916	0.158	0.109	0.076	1.107	1.049	0.728	0.584
Median	4346	0.853	0.904	0.949	0.118	0.083	0.048	1.058	1.050	0.745	0.595
Standard deviation	7938	0.140	0.097	0.092	0.110	0.081	0.077	0.128	0.022	0.177	0.211
Coefficient of variation	1.059	0.175	0.111	0.100	0.698	0.737	1.015	0.116	0.021	0.243	0.361
Maximum	38045	0.988	0.997	1.000	0.480	0.395	0.356	1.739	1.101	0.983	1.039
Minimum	498	0.414	0.528	0.573	0.011	0.003	0.000	1.001	0.973	0.012	0.010
No. of observation	167	166	166	166	166	166	166	166	166	166	166

(a) Statistics of RePLY and RCPLY measures are calculations based on the results of 166 countries, results of Tanzania are excluded.

(b) The last four columns on the right hand side are the statistics of the ratios, not the ratios of the statistics of the first six columns.

Table 3 Top and bottom 10 performers in terms of national average health status and health equality

	Average RePLY-DEA	Average RCPLY-DEA	Average RCPLY-SFA	RePLY-DEA Gini Coeff.	RCPLY-DEA Gini Coeff.	RCPLY-SFA Gini Coeff.
Top 10 countries	Japan	Yemen	Viet Nam	Japan	Yemen	Viet Nam
	Sweden	Japan	Yemen	Sweden	Japan	Yemen
(e.g. Japan has the higest average health status measured by RePLY-DEA, followed by Sweden; Yemen has the lowest RCPLY-DEA Gini coefficient, followed by Japan)	Switzerland	Viet Nam	Jamaica	Iceland	Viet Nam	Jamaica
	Australia	Sweden	Costa Rica	Switzerland	Sweden	Costa Rica
	Iceland	Australia	Syrian Arab Republic	Australia	Australia	Syrian Arab Republic
	Italy	Switzerland	Chile	Italy	Switzerland	Chile
	Canada	Iceland	Malta	Canada	Iceland	Malta
	France	Costa Rica	Sweden	France	Costa Rica	Sweden
	Spain	Spain	China	Spain	Spain	China
	Norway	Italy	Japan	Norway	Italy	Japan
Bottom 10 countries	Sierra Leone	Zimbabwe	Botswana	Sierra Leone	Angola	Angola
	Angola	Botswana	Zimbabwe	Angola	Swaziland	Swaziland
(e.g. Sierra Leone has the lowest average health status measured by RePLY-DEA, followed by Angola; Angola has the highest RCPLY-DEA Gini coefficient, followed by Swaziland)	Malawi	Angola	Swaziland	Malawi	Lesotho	Botswana
	Zambia	Swaziland	Angola	Niger	Zimbabwe	Sierra Leone
	Zimbabwe	Lesotho	Lesotho	Zambia	Sierra Leone	Zimbabwe
	Burundi	South Africa	Sierra Leone	Burkina Faso	Botswana	Lesotho
	Botswana	Zambia	South Africa	Burundi	Djibouti	South Africa
	Rwanda	Namibia	Zambia	Rwanda	Côte d'Ivoire	Namibia
	Lesotho	Sierra Leone	Namibia	Dem. Rep. of the Congo	Central African Republic	Zambia
	Swaziland	Djibouti	Central African Republic	Mali	Zambia	Central African Republic

Figure 1 Constructing the Global and Local Frontiers of Mortality Rates

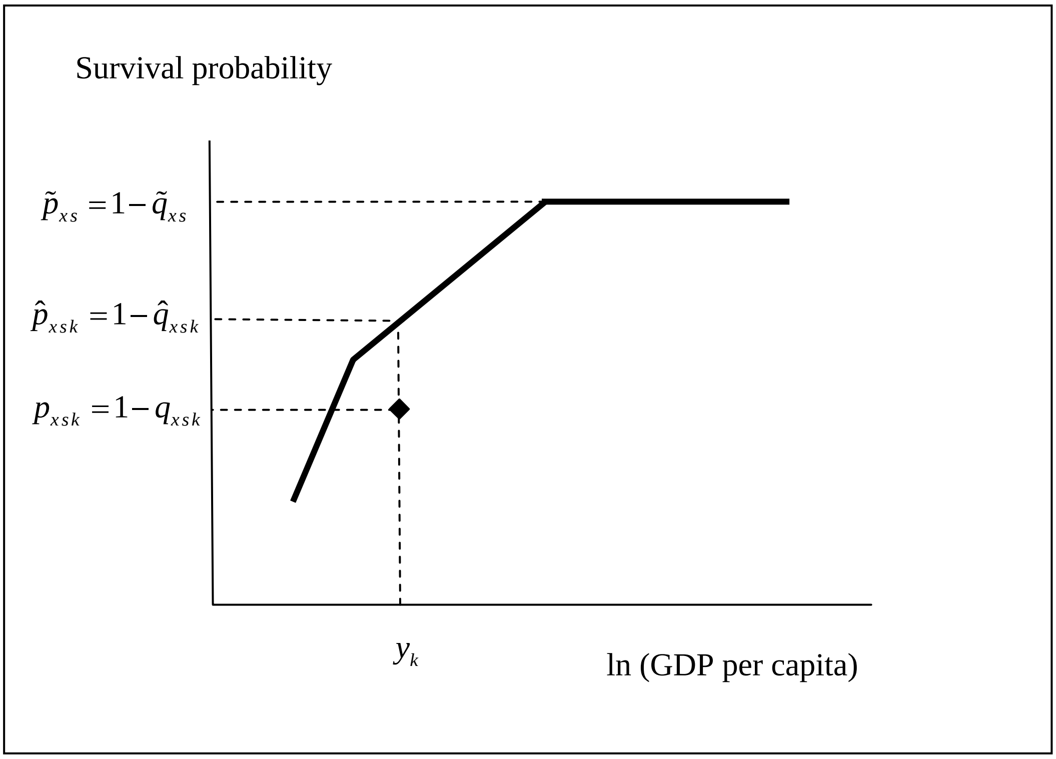


Figure 2 The DEA frontier of survival probability for males aged 75

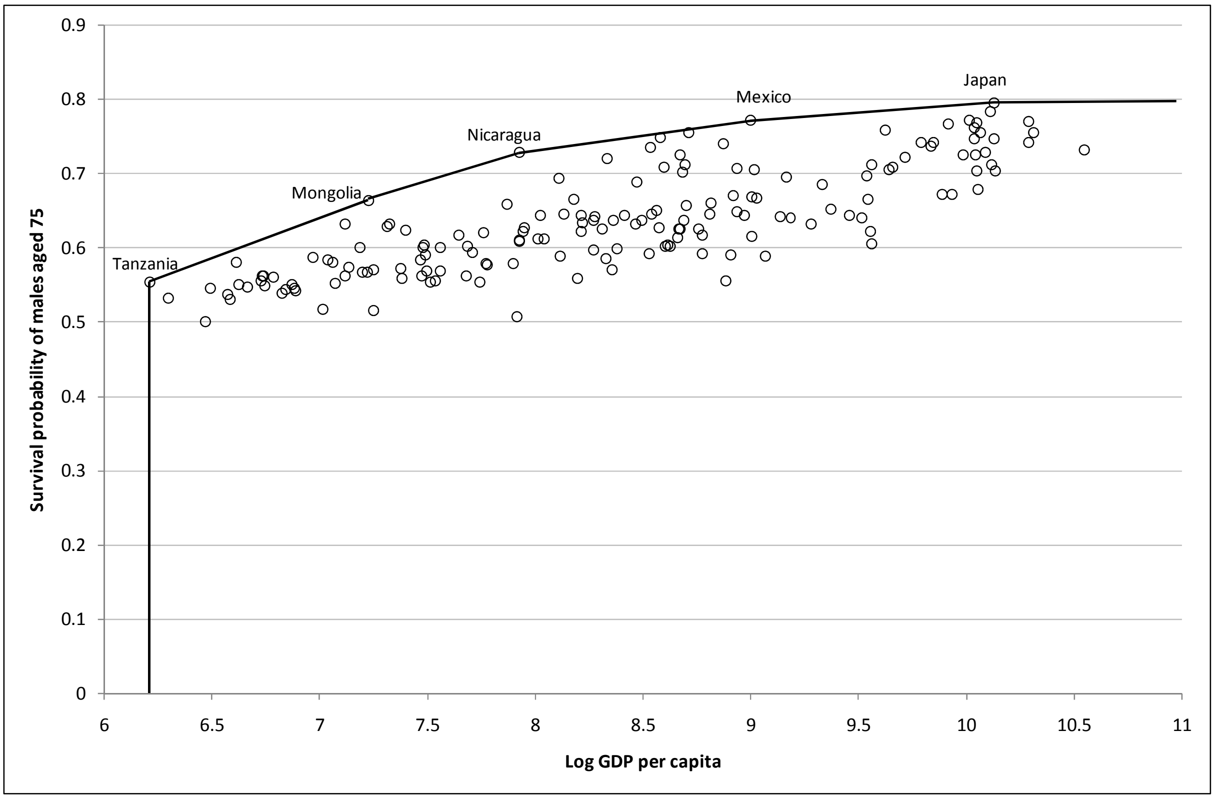


Figure 3 National Averages of RCPLY-DEA and RePLY-DEA

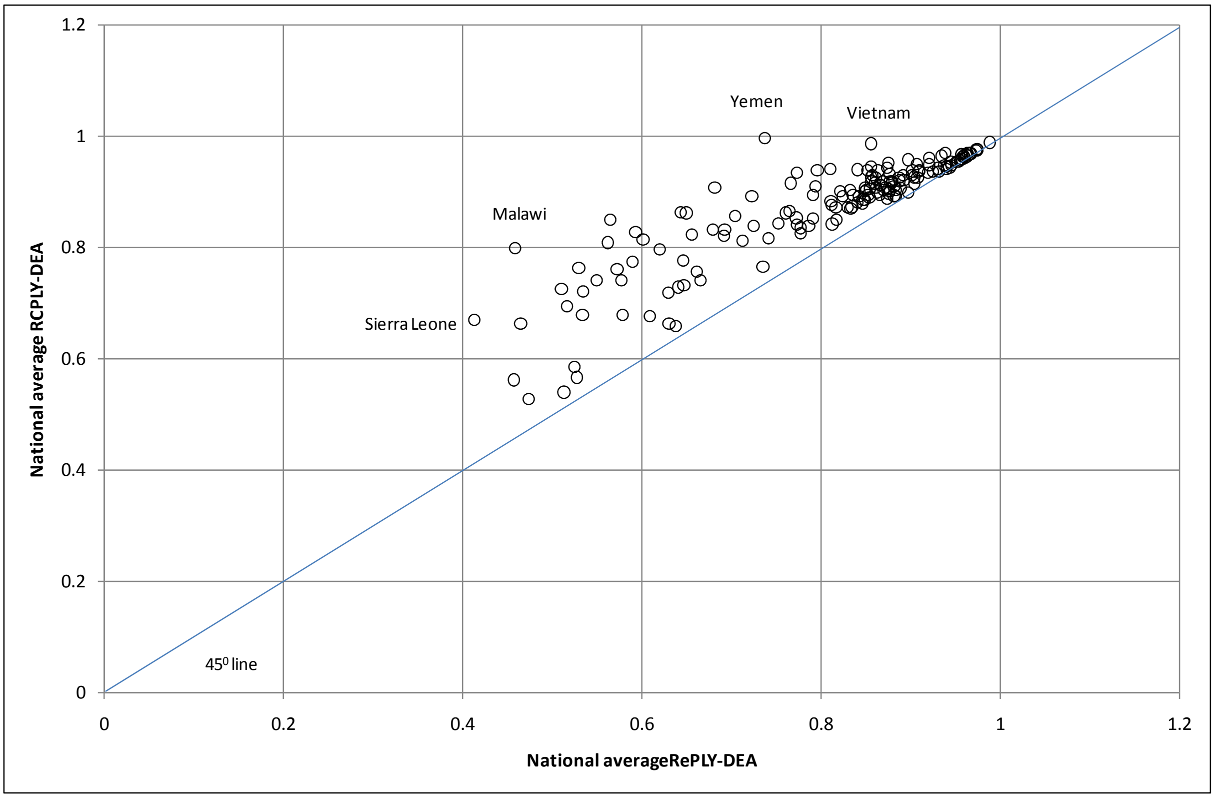


Figure 4 Gini Coefficients of RCPLY-DEA and RePLY-DEA

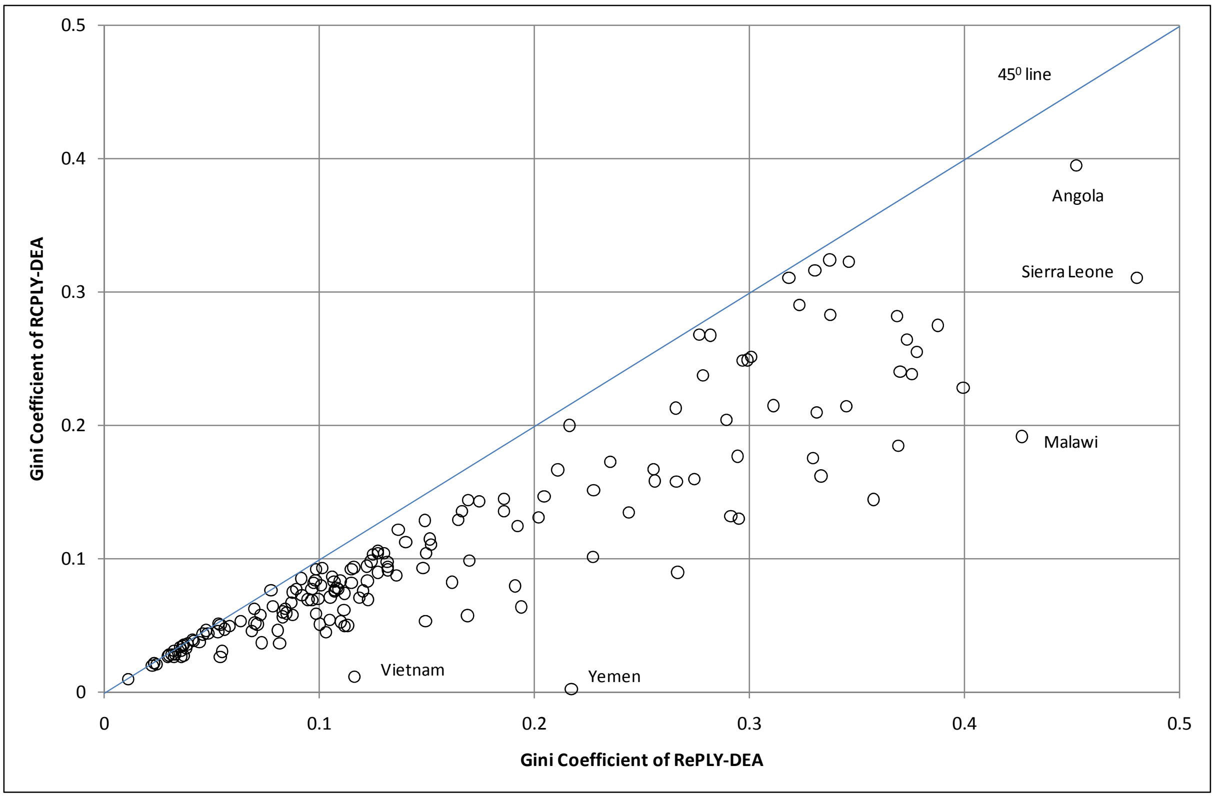


Figure 5 National Averages of RCPLY-SFA and RCPLY-DEA

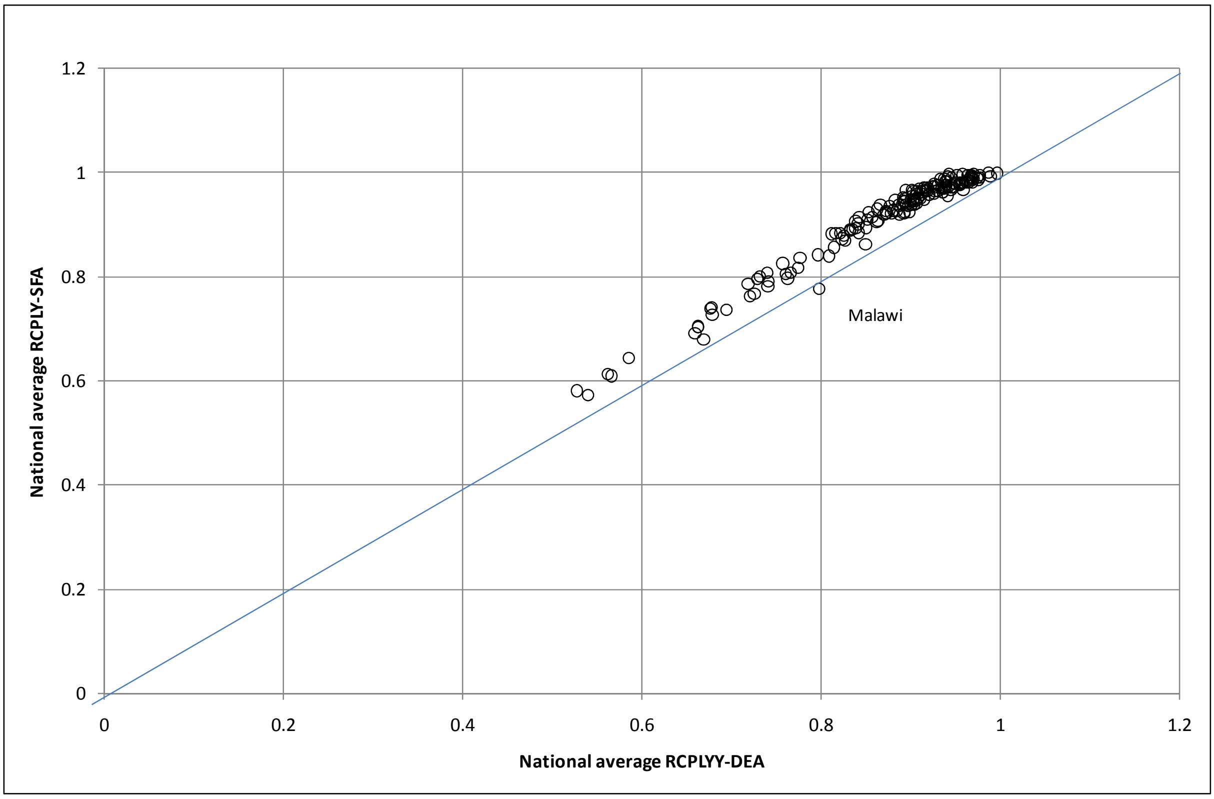


Figure 6 Gini Coefficients of RCPLY-SFA and RCPLY-DEA

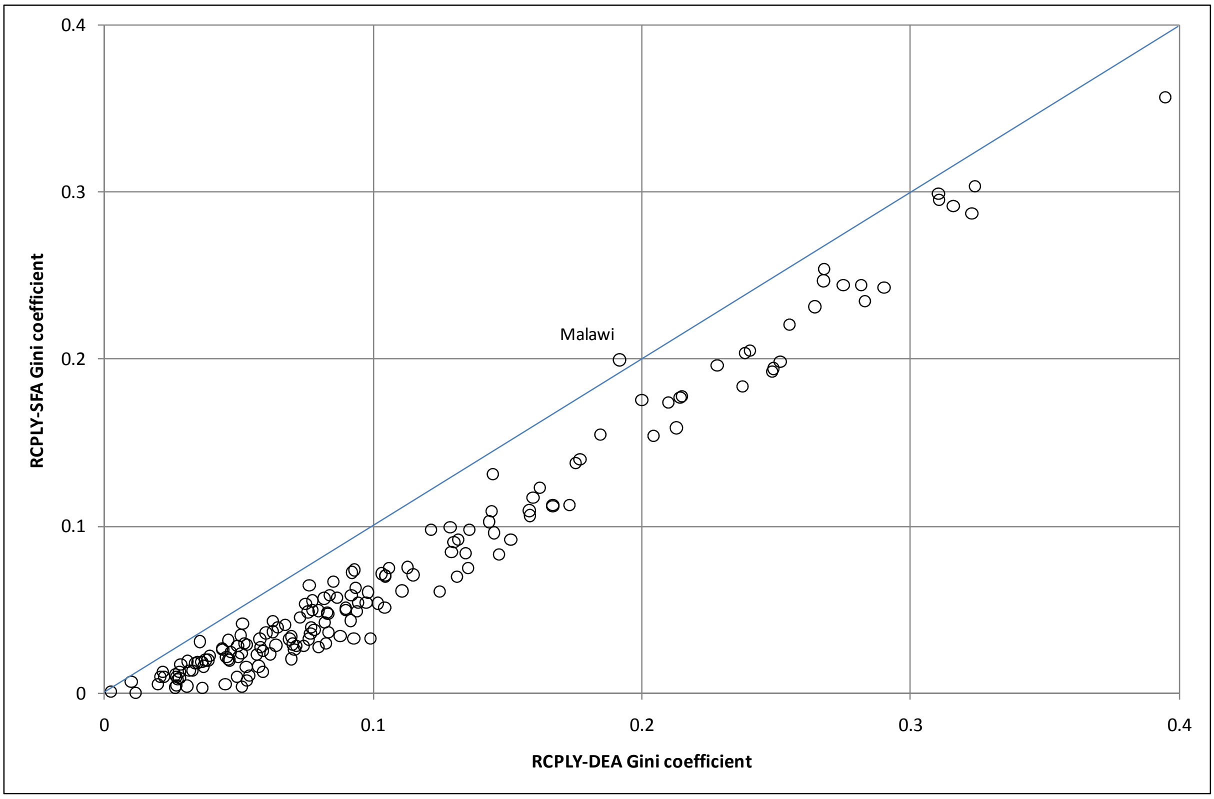


Figure 7 Gini Coefficient of RePLY-DEA and National Average RePLY-DEA

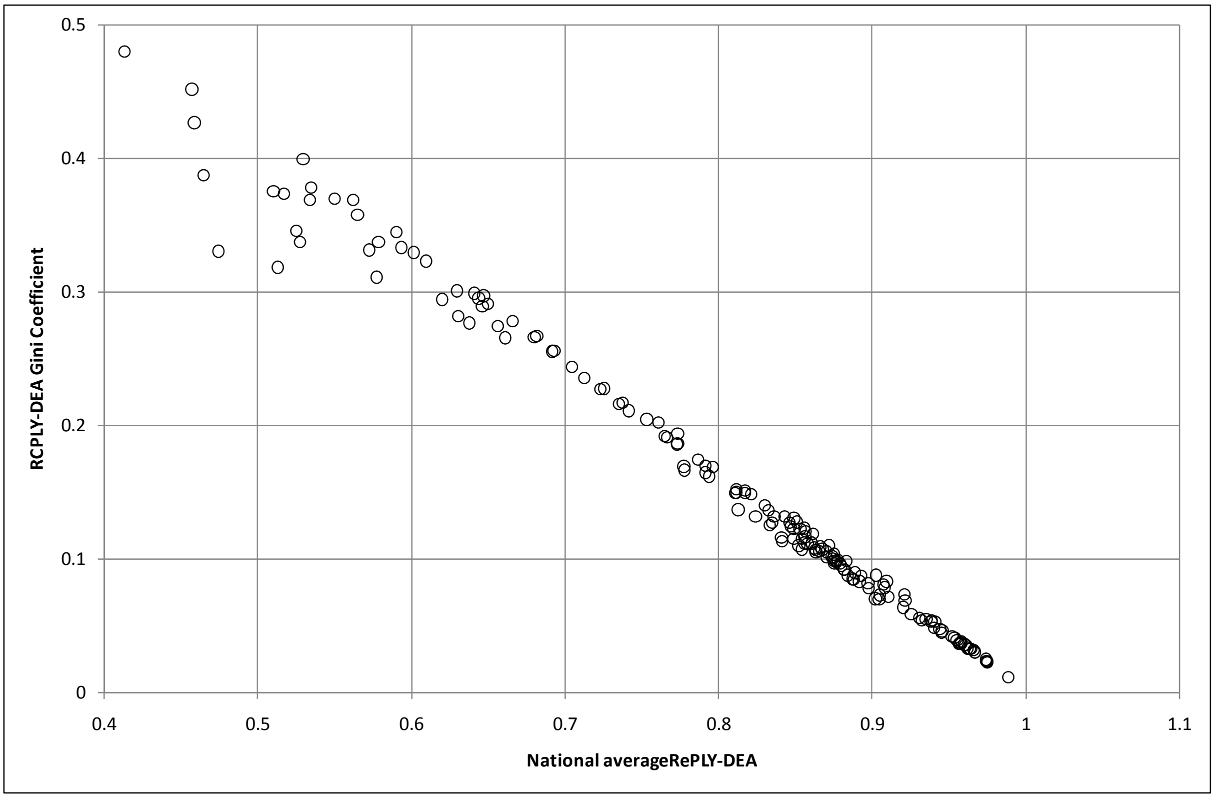


Figure 8 Gini Coefficient of RCPLY-DEA and National Average RCPLY-DEA

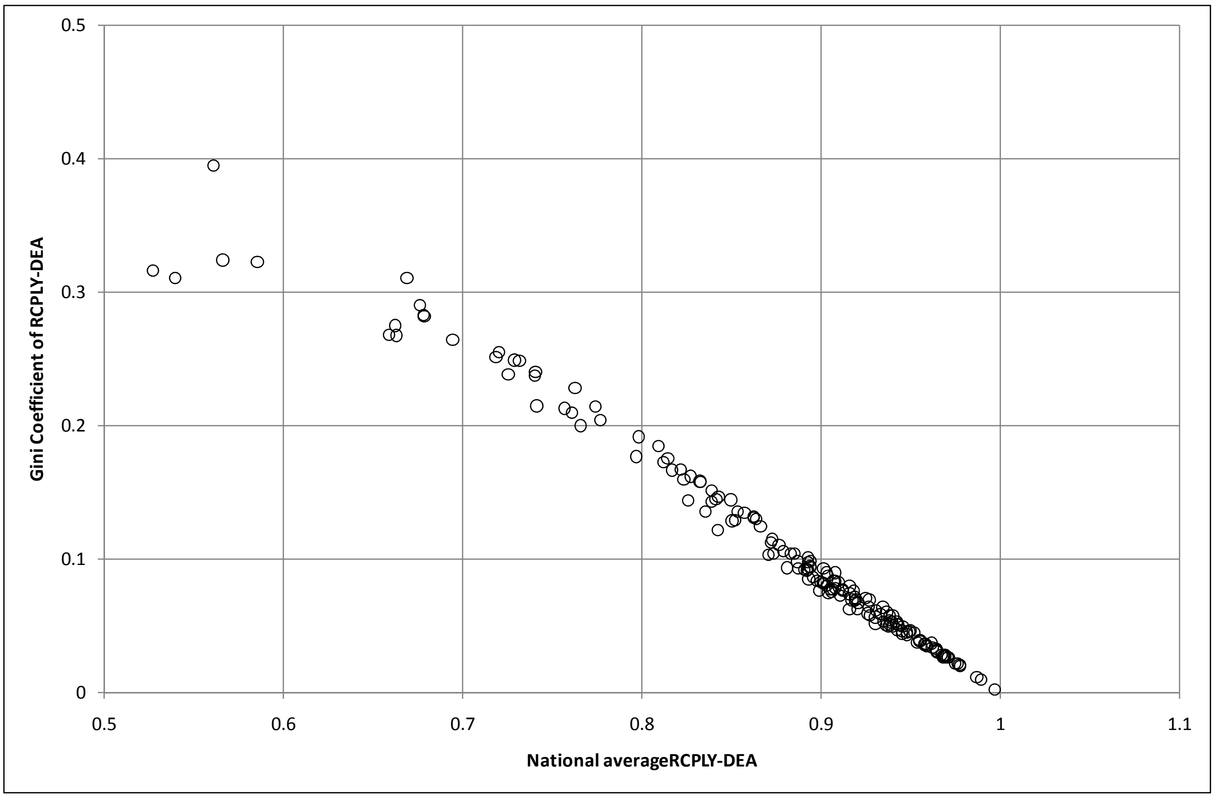
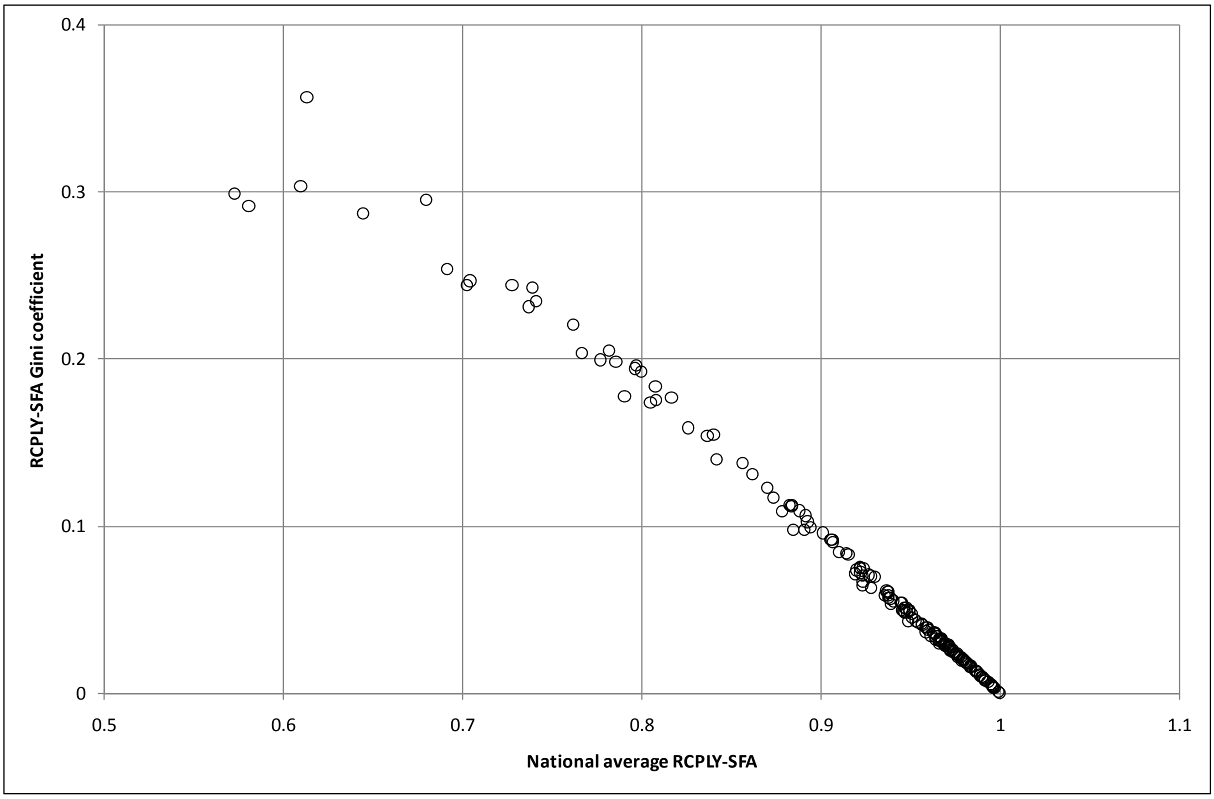


Figure 9 Gini Coefficient of RCPLY-SFA and National Average RCPLY-SFA



Appendix 1. Technical Notes on Frontier Estimation

1. Technical efficiency can be measured in either output orientation or input orientation. In the case of output orientation, the technical efficiency score is the actual output as a proportion of the maximum possible output for the given input. In the case of input orientation, the technical efficiency score is the minimum possible input that could produce the given output as a proportion of the actual input. In the current content of output being health status and input being income per capita, it is appropriate to use output orientation.

2. In the case of SFA, the significance of technical inefficiency can be tested using likelihood ratio (LR) test with Kodde and Palm critical values (Coelli et al 2005: pp.259).

3. In both DEA and SFA estimations, the TE scores are measured for individual age/sex groups. But they can be aggregated up using population size as the weight to a national TE score.

4. One disadvantage with using the WHO dataset is that many probabilities of death for each age/sex/country groups have been estimated and smoothed out using all available data. While this may sound advantageous it does leave us with the problem of not knowing the associated variance around each estimate, which is important to control for the heteroskedasticity present in our logit model. While not controlling for heteroskedasticity still results in unbiased (though inefficient) estimates for β_{1gx} and β_{2gx}, it results in biased estimates for the expectation of the one-sided error term conditional on the observed probably of survival given that σ_k^v varies across countries. Currently this problem is circumvented in the current paper by using the mode of the one sided error term instead of the expectation, though the expectation would provide

a better estimate. This problem can only be dealt with when we have information about σ_k^v.

5. Controlling for the heteroskedasticity in the frontier regression is also likely to help overcome the estimation issues experienced when too many explanatory variables are added.

Appendix 2. Full Estimation Results

country	GDP per capita (1990-99 average)	Average RePLY-DEA	Average RCPLY-DEA	Average RCPLY-SFA	RePLY-DEA Gini Coeff.	RCPLY-DEA Gini Coeff.	RCPLY-SFA Gini Coeff.	Average RePLY-DEA/average RCPLY-DEA	Average RCPLY-SFA/average RCPLY-DEA	RCPLY-DEA Gini coeff./RePLY-DEA Gini coeff.	RCPLY-SFA Gini coeff./RCPLY-DEA Gini coeff.
Albania	2728	0.864	0.939	0.989	0.105	0.054	0.010	1.087	1.053	0.516	0.192
Algeria	5113	0.853	0.894	0.945	0.122	0.094	0.054	1.048	1.057	0.772	0.571
Angola	1408	0.458	0.562	0.613	0.452	0.395	0.356	1.227	1.092	0.873	0.903
Antigua and Barbuda	9296	0.877	0.901	0.939	0.098	0.082	0.056	1.028	1.042	0.839	0.689
Argentina	11310	0.908	0.927	0.960	0.079	0.065	0.039	1.021	1.035	0.823	0.606
Armenia	2088	0.856	0.946	0.990	0.112	0.049	0.010	1.105	1.046	0.443	0.197
Australia	22285	0.974	0.978	0.990	0.025	0.021	0.009	1.004	1.013	0.860	0.448
Austria	25067	0.961	0.963	0.982	0.035	0.034	0.018	1.002	1.020	0.955	0.520
Azerbaijan	2762	0.773	0.842	0.901	0.186	0.145	0.096	1.088	1.071	0.779	0.661
Bahamas	15671	0.883	0.893	0.922	0.099	0.092	0.072	1.011	1.033	0.935	0.781
Bahrain	14218	0.904	0.916	0.949	0.070	0.063	0.043	1.013	1.036	0.901	0.685
Bangladesh	1321	0.767	0.916	0.972	0.191	0.080	0.027	1.195	1.061	0.417	0.343
Belarus	4346	0.854	0.906	0.947	0.107	0.076	0.048	1.061	1.045	0.708	0.637
Belgium	24050	0.954	0.956	0.977	0.041	0.039	0.022	1.002	1.023	0.960	0.562
Belize	4883	0.868	0.912	0.964	0.107	0.077	0.035	1.052	1.056	0.717	0.460
Benin	884	0.650	0.863	0.906	0.291	0.132	0.092	1.327	1.050	0.453	0.696
Bolivia	2227	0.773	0.854	0.924	0.186	0.136	0.074	1.104	1.082	0.729	0.549
Botswana	6357	0.514	0.540	0.573	0.318	0.310	0.299	1.051	1.062	0.974	0.962
Brazil	6746	0.846	0.879	0.922	0.127	0.106	0.075	1.039	1.049	0.832	0.704
Bulgaria	5822	0.887	0.927	0.973	0.085	0.059	0.025	1.044	1.050	0.698	0.422
Burkina Faso	935	0.535	0.721	0.762	0.378	0.255	0.220	1.347	1.057	0.675	0.863
Burundi	783	0.511	0.726	0.767	0.376	0.238	0.203	1.421	1.057	0.634	0.854
Cambodia	1409	0.692	0.822	0.884	0.255	0.167	0.113	1.188	1.075	0.653	0.675
Cameroon	1803	0.630	0.719	0.786	0.301	0.252	0.198	1.142	1.093	0.836	0.789
Canada	23528	0.967	0.969	0.988	0.030	0.028	0.012	1.003	1.019	0.929	0.439
Cape Verde	3682	0.849	0.907	0.963	0.123	0.084	0.036	1.069	1.061	0.682	0.433
Central African Republic	1179	0.534	0.679	0.728	0.369	0.282	0.244	1.271	1.072	0.764	0.866
Chad	850	0.602	0.815	0.856	0.330	0.175	0.138	1.354	1.051	0.532	0.785
Chile	7606	0.935	0.965	0.996	0.055	0.031	0.004	1.032	1.032	0.563	0.128
China	2608	0.875	0.952	0.995	0.103	0.045	0.005	1.088	1.045	0.436	0.112
Colombia	5963	0.872	0.909	0.951	0.110	0.083	0.048	1.042	1.047	0.759	0.570
Comoros	1789	0.765	0.867	0.938	0.192	0.125	0.061	1.133	1.082	0.650	0.486
Congo	1137	0.657	0.824	0.874	0.274	0.160	0.117	1.255	1.060	0.582	0.732
Costa Rica	7114	0.939	0.972	0.997	0.054	0.026	0.003	1.035	1.026	0.488	0.124
Côte d'Ivoire	1601	0.579	0.679	0.741	0.338	0.283	0.235	1.172	1.093	0.838	0.829
Croatia	8136	0.902	0.931	0.966	0.070	0.052	0.030	1.032	1.038	0.742	0.569
Cyprus	16579	0.945	0.954	0.979	0.044	0.038	0.020	1.009	1.026	0.852	0.521
Czech Republic	13944	0.925	0.938	0.969	0.059	0.050	0.028	1.014	1.033	0.850	0.564
Dem. Rep. of the Congo	918	0.550	0.741	0.782	0.370	0.240	0.205	1.346	1.056	0.649	0.852
Denmark	25144	0.944	0.945	0.967	0.048	0.046	0.031	1.002	1.022	0.972	0.677
Djibouti	2299	0.610	0.676	0.739	0.323	0.290	0.243	1.109	1.093	0.897	0.837
Dominica	5072	0.907	0.950	0.980	0.081	0.047	0.019	1.047	1.032	0.577	0.418
Dominican Republic	5040	0.830	0.873	0.922	0.140	0.113	0.075	1.051	1.057	0.805	0.665
Ecuador	3318	0.861	0.925	0.974	0.119	0.071	0.026	1.074	1.053	0.598	0.365
Egypt	3020	0.824	0.892	0.953	0.132	0.092	0.043	1.083	1.068	0.695	0.471
El Salvador	4169	0.851	0.903	0.948	0.128	0.090	0.051	1.061	1.049	0.705	0.565
Equatorial Guinea	2163	0.666	0.741	0.808	0.278	0.238	0.183	1.112	1.091	0.853	0.772
Eritrea	1115	0.578	0.742	0.791	0.311	0.215	0.177	1.284	1.066	0.691	0.825
Estonia	7596	0.876	0.906	0.945	0.097	0.078	0.050	1.034	1.044	0.803	0.641

Ethiopia	751	0.594	0.828	0.870	0.333	0.162	0.123	1.394	1.051	0.487	0.758
Fiji	4748	0.862	0.908	0.960	0.108	0.078	0.037	1.054	1.057	0.723	0.479
Finland	21731	0.952	0.956	0.980	0.042	0.039	0.020	1.004	1.025	0.928	0.507
France	23090	0.966	0.970	0.983	0.032	0.029	0.017	1.004	1.014	0.902	0.595
Gabon	6467	0.735	0.766	0.808	0.216	0.200	0.175	1.042	1.055	0.925	0.876
Gambia	1594	0.725	0.839	0.906	0.228	0.151	0.092	1.157	1.080	0.665	0.605
Georgia	2174	0.852	0.940	0.984	0.110	0.053	0.016	1.103	1.047	0.481	0.293
Germany	22971	0.955	0.958	0.981	0.039	0.036	0.018	1.003	1.024	0.939	0.504
Ghana	1745	0.713	0.812	0.883	0.235	0.173	0.112	1.139	1.087	0.735	0.650
Greece	15076	0.957	0.969	0.992	0.037	0.028	0.008	1.012	1.024	0.743	0.301
Grenada	5759	0.833	0.871	0.919	0.125	0.103	0.071	1.045	1.056	0.827	0.689
Guatemala	3685	0.817	0.873	0.927	0.151	0.115	0.071	1.069	1.061	0.760	0.615
Guinea	1826	0.641	0.729	0.796	0.299	0.249	0.194	1.137	1.092	0.832	0.780
Guinea-Bissau	982	0.590	0.775	0.817	0.345	0.214	0.177	1.312	1.054	0.621	0.825
Guyana	3343	0.792	0.852	0.910	0.165	0.129	0.084	1.077	1.068	0.786	0.651
Haiti	1761	0.661	0.757	0.826	0.266	0.213	0.159	1.145	1.091	0.801	0.745
Honduras	2829	0.832	0.904	0.965	0.136	0.088	0.034	1.086	1.068	0.646	0.388
Hungary	10713	0.884	0.905	0.939	0.088	0.075	0.053	1.023	1.038	0.855	0.710
Iceland	24651	0.974	0.975	0.990	0.023	0.022	0.010	1.001	1.015	0.947	0.437
India	1917	0.753	0.843	0.915	0.205	0.147	0.083	1.119	1.086	0.719	0.561
Indonesia	2768	0.812	0.883	0.947	0.150	0.104	0.051	1.089	1.072	0.697	0.487
Iran (Islamic Republic of)	5282	0.847	0.887	0.937	0.124	0.098	0.060	1.048	1.056	0.791	0.612
Ireland	19634	0.940	0.946	0.972	0.048	0.044	0.026	1.006	1.028	0.914	0.581
Israel	20289	0.960	0.965	0.987	0.036	0.032	0.013	1.005	1.023	0.886	0.411
Italy	22864	0.967	0.970	0.990	0.029	0.027	0.010	1.003	1.021	0.913	0.357
Jamaica	3562	0.897	0.959	0.997	0.082	0.037	0.003	1.069	1.040	0.447	0.082
Japan	24980	0.988	0.990	0.993	0.011	0.010	0.007	1.001	1.004	0.894	0.639
Jordan	3923	0.877	0.933	0.987	0.099	0.059	0.013	1.064	1.058	0.599	0.213
Kazakhstan	4260	0.778	0.826	0.879	0.169	0.144	0.109	1.063	1.063	0.851	0.755
Kenya	1060	0.620	0.797	0.842	0.294	0.177	0.140	1.286	1.056	0.601	0.789
Kiribati	3902	0.787	0.839	0.893	0.174	0.143	0.103	1.067	1.064	0.821	0.716
Kuwait	20562	0.932	0.937	0.962	0.054	0.051	0.034	1.005	1.027	0.938	0.680
Kyrgyzstan	1636	0.794	0.910	0.969	0.162	0.083	0.030	1.146	1.065	0.510	0.361
Lao People's Dem. Republic	1233	0.680	0.833	0.888	0.266	0.158	0.109	1.225	1.066	0.594	0.690
Latvia	6710	0.870	0.904	0.947	0.101	0.080	0.049	1.038	1.047	0.791	0.614
Lebanon	3914	0.861	0.916	0.971	0.112	0.074	0.028	1.065	1.060	0.666	0.377
Lesotho	2387	0.525	0.586	0.645	0.346	0.323	0.287	1.115	1.101	0.933	0.890
Lithuania	8345	0.893	0.921	0.957	0.087	0.068	0.041	1.032	1.039	0.776	0.601
Luxembourg	38045	0.958	0.959	0.968	0.037	0.036	0.031	1.002	1.009	0.963	0.854
Madagascar	842	0.682	0.908	0.950	0.267	0.090	0.050	1.332	1.046	0.337	0.554
Malawi	543	0.459	0.799	0.777	0.427	0.192	0.199	1.739	0.973	0.449	1.039
Malaysia	7195	0.888	0.921	0.959	0.084	0.063	0.037	1.037	1.041	0.747	0.583
Mali	713	0.563	0.810	0.840	0.369	0.184	0.155	1.439	1.038	0.500	0.839
Malta	14225	0.957	0.968	0.996	0.036	0.027	0.004	1.012	1.028	0.748	0.157
Mauritania	1875	0.647	0.732	0.800	0.297	0.249	0.192	1.131	1.093	0.837	0.773
Mauritius	7848	0.882	0.911	0.951	0.092	0.073	0.045	1.034	1.044	0.792	0.616
Mexico	8080	0.909	0.937	0.964	0.083	0.060	0.036	1.030	1.028	0.725	0.595
Micronesia (Fed. States of)	6477	0.817	0.851	0.895	0.149	0.129	0.099	1.041	1.051	0.864	0.770
Mongolia	1375	0.796	0.940	0.984	0.169	0.057	0.016	1.181	1.046	0.340	0.278
Morocco	3408	0.857	0.919	0.968	0.121	0.076	0.032	1.072	1.053	0.632	0.421
Mozambique	661	0.565	0.850	0.862	0.358	0.145	0.131	1.504	1.014	0.405	0.903
Namibia	5578	0.631	0.663	0.704	0.282	0.268	0.247	1.052	1.062	0.949	0.922
Nepal	1165	0.723	0.893	0.945	0.227	0.102	0.054	1.235	1.059	0.448	0.526
Netherlands	24716	0.958	0.959	0.981	0.037	0.035	0.018	1.002	1.023	0.957	0.517
New Zealand	17866	0.958	0.964	0.986	0.038	0.033	0.013	1.007	1.023	0.857	0.408
Nicaragua	2767	0.856	0.927	0.979	0.123	0.070	0.020	1.083	1.056	0.566	0.293

Niger	723	0.530	0.763	0.797	0.400	0.228	0.196	1.440	1.044	0.571	0.860
Nigeria	844	0.644	0.864	0.907	0.295	0.130	0.090	1.342	1.049	0.441	0.693
Norway	29307	0.963	0.965	0.981	0.033	0.031	0.019	1.002	1.016	0.951	0.604
Oman	11727	0.889	0.907	0.941	0.090	0.078	0.055	1.020	1.037	0.866	0.710
Pakistan	1773	0.761	0.863	0.930	0.202	0.131	0.069	1.134	1.078	0.649	0.528
Panama	5331	0.921	0.962	0.984	0.073	0.037	0.016	1.045	1.023	0.507	0.429
Papua New Guinea	2371	0.742	0.817	0.884	0.211	0.167	0.112	1.102	1.082	0.791	0.669
Paraguay	4513	0.870	0.919	0.971	0.105	0.072	0.028	1.056	1.057	0.680	0.391
Peru	4277	0.843	0.893	0.945	0.132	0.098	0.054	1.059	1.058	0.741	0.554
Philippines	3707	0.836	0.895	0.950	0.132	0.094	0.049	1.070	1.062	0.714	0.517
Poland	8140	0.911	0.939	0.975	0.071	0.051	0.024	1.031	1.038	0.716	0.461
Portugal	15415	0.938	0.948	0.978	0.053	0.046	0.021	1.011	1.032	0.859	0.467
Republic of Korea	12771	0.920	0.935	0.969	0.063	0.053	0.029	1.017	1.036	0.837	0.546
Republic of Moldova	1921	0.841	0.941	0.977	0.113	0.050	0.022	1.118	1.039	0.442	0.432
Romania	5988	0.880	0.918	0.964	0.095	0.070	0.034	1.043	1.051	0.735	0.484
Russian Federation	7373	0.813	0.843	0.885	0.137	0.122	0.098	1.037	1.050	0.890	0.801
Rwanda	974	0.517	0.695	0.737	0.373	0.264	0.231	1.344	1.060	0.708	0.874
Saint Kitts and Nevis	9570	0.875	0.898	0.936	0.098	0.084	0.059	1.026	1.042	0.853	0.699
Saint Lucia	5412	0.879	0.920	0.966	0.097	0.069	0.032	1.046	1.051	0.715	0.465
Saint Vincent and Grenadines	4763	0.867	0.913	0.959	0.109	0.077	0.039	1.053	1.051	0.708	0.505
Samoa	4072	0.849	0.902	0.955	0.115	0.082	0.042	1.063	1.058	0.715	0.510
Sao Tome and Principe	1777	0.791	0.895	0.967	0.170	0.099	0.033	1.131	1.081	0.582	0.330
Saudi Arabia	13521	0.874	0.888	0.920	0.102	0.093	0.073	1.016	1.036	0.916	0.789
Senegal	1338	0.693	0.833	0.892	0.256	0.158	0.106	1.202	1.071	0.619	0.670
Seychelles	14074	0.882	0.894	0.924	0.092	0.085	0.066	1.013	1.034	0.928	0.778
Sierra Leone	645	0.414	0.669	0.680	0.480	0.310	0.295	1.617	1.016	0.647	0.951
Singapore	18674	0.962	0.968	0.991	0.033	0.028	0.009	1.006	1.024	0.856	0.317
Slovakia	9745	0.905	0.927	0.965	0.073	0.058	0.032	1.025	1.040	0.796	0.555
Slovenia	13840	0.931	0.943	0.974	0.056	0.047	0.024	1.013	1.033	0.846	0.517
Solomon Islands	2346	0.822	0.902	0.968	0.148	0.093	0.032	1.098	1.073	0.626	0.348
South Africa	8687	0.638	0.660	0.692	0.277	0.268	0.254	1.034	1.049	0.968	0.948
Spain	18901	0.964	0.971	0.989	0.033	0.027	0.011	1.007	1.019	0.818	0.406
Sri Lanka	2814	0.858	0.931	0.976	0.112	0.062	0.023	1.085	1.048	0.554	0.378
Sudan	1255	0.705	0.858	0.914	0.244	0.135	0.084	1.217	1.066	0.552	0.622
Suriname	5520	0.835	0.874	0.923	0.127	0.105	0.070	1.046	1.057	0.822	0.671
Swaziland	4130	0.528	0.567	0.610	0.337	0.324	0.303	1.073	1.076	0.960	0.936
Sweden	22776	0.975	0.978	0.995	0.022	0.020	0.005	1.003	1.018	0.895	0.245
Switzerland	29381	0.975	0.976	0.987	0.024	0.022	0.013	1.002	1.011	0.932	0.579
Syrian Arab Republic	3042	0.874	0.944	0.996	0.100	0.051	0.004	1.079	1.056	0.510	0.070
Tajikistan	1233	0.774	0.935	0.972	0.194	0.064	0.028	1.209	1.039	0.330	0.443
TFYR Macedonia	5812	0.892	0.931	0.976	0.083	0.057	0.023	1.044	1.048	0.685	0.401
Thailand	5834	0.849	0.886	0.928	0.130	0.105	0.070	1.043	1.048	0.801	0.667
Togo	1365	0.646	0.777	0.837	0.289	0.204	0.154	1.202	1.077	0.706	0.754
Tonga	5939	0.863	0.900	0.948	0.107	0.083	0.048	1.043	1.053	0.778	0.580
Trinidad and Tobago	7444	0.866	0.896	0.938	0.106	0.087	0.057	1.035	1.047	0.819	0.658
Tunisia	5233	0.878	0.920	0.970	0.099	0.070	0.029	1.048	1.055	0.706	0.417
Turkey	5907	0.854	0.891	0.938	0.115	0.092	0.058	1.043	1.052	0.800	0.633
Turkmenistan	3625	0.778	0.836	0.891	0.166	0.136	0.098	1.075	1.066	0.818	0.718
Uganda	965	0.573	0.761	0.805	0.331	0.210	0.174	1.329	1.057	0.633	0.827
Ukraine	5453	0.841	0.881	0.928	0.116	0.094	0.063	1.048	1.053	0.807	0.672
United Arab Emirates	23221	0.897	0.900	0.923	0.078	0.076	0.064	1.002	1.027	0.983	0.840
United Kingdom	23122	0.946	0.948	0.972	0.046	0.044	0.027	1.003	1.025	0.952	0.611
United States of America	30154	0.941	0.942	0.956	0.053	0.052	0.041	1.002	1.015	0.972	0.805
Uruguay	8229	0.921	0.950	0.980	0.069	0.046	0.020	1.031	1.031	0.671	0.435
Uzbekistan	1497	0.811	0.943	0.992	0.149	0.053	0.008	1.162	1.053	0.357	0.143
Vanuatu	3110	0.812	0.877	0.937	0.152	0.111	0.061	1.080	1.068	0.729	0.551

Venezuela	6076	0.902	0.939	0.973	0.088	0.058	0.027	1.040	1.036	0.664	0.468
Viet Nam	1516	0.856	0.987	1.000	0.117	0.012	0.000	1.153	1.013	0.100	0.010
Yemen	743	0.738	0.997	0.999	0.217	0.003	0.001	1.352	1.002	0.012	0.240
Zambia	836	0.465	0.663	0.703	0.388	0.275	0.244	1.425	1.060	0.709	0.888
Zimbabwe	2682	0.475	0.528	0.581	0.331	0.316	0.291	1.112	1.101	0.955	0.923