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Publication date:
2009

Dundee Discussion Papers in Economics

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Working Paper
No. 224
July 2009
ISSN:1473-236X

Measuring Avoidable Health Inequality with Realization of Conditional Potential Life Years (RCPLY)

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This version: July 2009

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 (AAD), and its associated health inequality indicators that measure the distribution of AAD. 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). 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

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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 (AAD), i.e. length-of-life. In fact, AAD was one of the first indicators used to measure health inequality (Le Grand 1987, 1989).

Using AAD 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 AAD. Thirdly, vital statistics are one of the mostly commonly collected data, even in many developing countries. As a result, AAD 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, AAD 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, AAD 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 AAD of avoidable death (i.e. age-at-avoidable-death) has been recently introduced by Tang, Chin and Rao (TCR) (2008) to

[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.

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 AAD as a proportion of their potential AAD. 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 AAD 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 AAD 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 approach is that the frontier profile of mortality rates are, as expected, determined by the mortality rates of mostly

[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.

high income countries. This means that the health performance of low income countries is benchmarked against that of their affluent counterparts.

It is unrealistic, however, to expect that the government of poorer countries could provide the same level of health care 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. On the other hand, if our interest is on health inequality within countries rather than global health inequality, 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 the current paper is, therefore, to develop a health status indicator that takes into account the short term resource constraints faced by countries, and use it to measure health inequality within countries.

To achieve this objective, we modify the RePLY measure in the following way. 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 AAD or RePLY.

We will estimate in total three health status measures, namely AAD, RePLY, and RCPLY. Simply put, AAD is health indicator based on total mortality risks; RePLY distinguishes between avoidable and unavoidable mortality risks; and RCPLY distinguishes between unconditional unavoidable, conditional unavoidable and conditional avoidable mortality risks. The relationships between these risk components are shown in Figure 1. A comparative analysis of the findings from the three measures can be used in gauging the importance of controlling for unavoidable mortality risks and resources respectively.

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 the DEA method. Section 4 discusses issues involved in measuring health inequality when the health variables are of bounded values, as in the case of RePLY and RCPLY, and to a less extent, of AAD. 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.

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

Avoidable and unavoidable mortality risks in this section all refer to the unconditional ones (see Figure 1). We omit the term "unconditional" till the next section for easy of expression.

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 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 waves, 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 three aspects: genetic factors, resources, and technology.[3]

[3] One can argue that chance or luck is the fourth aspect.

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 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 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, the method 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.

[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.

[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.

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[6], TCR construct a hypothetical frontier country that has the lowest 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}.[7] 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

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

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

[6] This method is like the DEA method used in this paper, except that it does not involve any input and production function.

[7] 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.

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)[8]

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. AAD) to his potential length-of-life. For an avoidable 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.[9] 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:

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

[8] This section is drawn from Tang, Petrie & Rao (2006).

[9] 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*.

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

$$U_{xsk} = N_{xsk}\,\tilde{q}_{xs} \tag{3}$$

where N_{xsk} is the size of the group in the stationary population[10].

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

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

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.

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. While the RePLY concept can be used to measure inequality across other dimensions, such as income or education, life tables only stratify a population by age and sex, therefore with the current data this is not possible. Besides this data-related constraint, RePLY has a methodology-related limitation in that it assumes that unavoidable mortality risks are country invariant. The new measure introduced in the next section addresses this limitation.

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

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 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- and non-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. Therefore, in the current paper we decide against including education level or education expenditure.

Since we estimate the frontier for each individual age-sex group, ideally it requires group specific resources, which is simply not available even for developed countries. This could potentially create a problem that, even at the same income level, theoretically different countries could allocate a disproportionally large amount of resources into the most preferred group and lowers the benchmark mortality rate to a very low level for that group. If different countries have different preferred groups, then the resulting mortality profile of the constructed frontier country will be unattainable by most age-sex groups at the same time with the given income level. Nevertheless, since there are strong diminishing returns to health spending when the mortality rate is very low, it is unlikely that a government will allocate an excessive amount of resources to just a few age-sex groups as they will be more than punished with excessive avoidable mortality in those age-sex groups that receive fewer resources.

Lastly, countries in different parts of the world are exposed to very different kinds of climate and biophysical environments 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 these 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 the data envelopment method as it requires a prior knowledge on the direction of the contribution of an input factor to output.[11] 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 unconditional 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*

[11] The stochastic frontier method does not require such a prior knowledge but still requires a specified functional form, and again confronts the aforementioned model sensitivity issue.

unavoidable mortality risks are age, sex and country specific[12]*, and time variant (as technology and available resources 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:

$$p_{xs} = f_{xs}(y) \tag{5}$$

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 estimation. This is because, although we already use log income as the input, the underlying relationship between 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

[12] 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.

We demonstrate the concepts using Figure 2. 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:

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

By definition, we have $p_{xsk} \leq \hat{p}_{xsk} \leq \tilde{p}_{xs} \Rightarrow q_{xsk} = 1 - p_{xsk} \geq 1 - \hat{p}_{xsk} = \hat{q}_{xsk} \geq 1 - \tilde{p}_{xs} = \tilde{q}_{xs}$. Mortality risk $\hat{q}_{xsk}$ is the lowest mortality risk projected from observed countries with income levels around y_k.[13] 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:

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

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 "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.

[13] 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.

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

$$U^{C}_{xsk} = N_{xsk}(\hat{q}_{xsk} - \tilde{q}_{xsk}) \quad (8)$$

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

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

3.2.4 Reasons for conditional avoidable mortality

There are a number of reasons why conditional avoidable mortality may exist at certain age-sex groups. First, a smaller amount of health-related resources may be devoted to this age-sex group compared to that allocated by other countries with similar amounts of total resources, and secondly, these health-related resources may not be being used as efficiency as other countries with similar amounts of resources. In terms of inefficiency this may include allocative inefficiency in the sense that the resources are not being used to prevent the most cost-effective deaths in this age-sex group[14] or this may include technical inefficiency in the sense that the country is inefficient at using the allocated resources.

In Figure 2, the higher the survival probability attained by a country relative to the maximum observed survival probability at its income level (i.e. $p_{xsk} / \hat{p}_{xsk}$) is, the better the country is in treating the group in concern. By definition, we have $0 \le p_{xsk} / \hat{p}_{xsk} \le 1$. Countries that lie on the frontier are considered as the best performer conditional on the total resources that they have. An important point is that country k is benchmarked against and compared with the best performing countries with similar income levels.

[14] This infers that some individuals who were not cost-effective to save from death, given their countries resources, achieve an actual RCPLY greater than 1 and this offsets some of the individuals who were cost-effective to save but died from insufficient resources. The RCPLY, however, only encompasses those additional numbers of deaths that could have been saved if only those most cost-effective deaths were saved. If additional life table data which is broken up into more detailed groups, such as income classes, rather than just age-sex then this could be used to measure these additional inequalities. In this sense the RCPLY for each age-sex group only represents the average RCPLY.

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). Using SFA, however, provides additional complexities and, therefore, in the current paper we focus on the results from the DEA method in order to better illustrate the concepts.

4.1 Estimating the frontier using the Data Envelopment Analysis (DEA) Method

The DEA method constructs a frontier using a piecewise linear frontier similar to the one drawn in Figure 2.[15] 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.[16] This is illustrated in Figure 3 using the survival probabilities of males aged 75 for the 167 countries. This age-sex group is selected because there is large variation in the survival probabilities across countries that make the visual identification of the frontier clearer. For this age-sex group the data envelopment method has identified five countries with top performance given their total resources available, Tanzania (United Republic of), 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 these peers' mortality rates. Amongst these five countries, Japan has the highest survival probability; therefore, it is the only country that has zero both conditional and unconditional avoidable mortality risks for this age-sex group.

[15] The frontier can be estimated in either output orientation or input orientation. In the case of output orientation, countries are supposed to maximize outputs using given inputs; in the case of input orientation, countries are supposed minimize inputs for given output targets. In the current content of output being health status and input being income per capita, it is appropriate to use output orientation.

[16] It is necessary to use linear programming methods to identify the frontier and there by calculating technical efficiencies when multiple inputs and/or multiple outputs are present. Details of the general DEA methodology can be found in Coelli, Rao, O'Donnell and Battese (2005).

Tanzania is a special case worth mentioning. It sits on the "edge" of the frontier mainly because it has the lowest income level ($498, PPP, constant year 2000 international dollars) amongst all the countries in the dataset.[17] Due to its status of having the lowest income, even if its survival probability drops to very low, it will remain on the frontier. In fact, this is the case for all age-sex groups, making Tanzania 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 frontier estimation procedure, no meaningful conclusions can be draw about Tanzania. Despite this, Tanzania is kept in the estimation, otherwise, the same situation would hold for the country with the second lowest income level in the sample.

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. Countries are listed according to their incomes, with the poorest being the first. The lists of countries are noticeably lengthy, especially for ages below 30. A long list reflects a more continuous convex frontier, indicating that controlling for income is important in considering the achievable mortality rates of a country. 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 compared to other factors and natural variation. The second explanation is that if people of lower income are more likely to die prematurely, then those who survive to the old age, even in countries of low average income, could be wealthier than what the national average income indicates. The third possible explanation is that, related to the second one, unhealthy people in low income countries could die earlier more easily than in high income countries, so their older age groups are populated more by the healthy one. For instance, although Mexico has noticeably higher infants and children mortality rates than other OECD countries, its elderly outperforms their counterparts, as demonstrated in Figure 3.

[17] 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.

If cohort lifetables were available rather than cross-sectional lifetables then this problem could be addressed by using the cumulative mortality profile for each age-sex group, however, standardized cohort lifetables are not available for most countries.

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 performance of their health systems given the available resources. The performance 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 would need to control for the amount of national resources spent on health. We leave this issue for further research.

5. Inequality Measures

Once we obtain the estimates of AAD, RePLY and RCPLY for each age-sex group, we can assessment the degree of health inequality within a country. It should be reiterated that due to the nature of life tables, we can only stratify the population along age and sex dimensions, and, in the case of RePLY and RCPLY, the avoidable/unavoidable death dimension only. There are numerous inequality indicators that can be used to illustrate the distribution of health. In this paper, we focus on the Gini coefficient.

In the inter-individual difference approach, the Gini coefficient is equal to the total absolute pair-wise difference in individual attribute (e.g. income or health), standardized by the maximal total absolute pair-wise difference that is possible conditional on the total attribute of the population. When the attribute can be freely reallocated amongst individuals like income, the maximal total absolute pair-wise difference is achieved when one person has all the attributes and all others have none. Hence, the Gini coefficient is given by

$$G = \frac{\sum_{i}^{n}\sum_{j}^{n}\left|y_i - y_j\right|}{2\sum_{i}^{n-1}\left|n\bar{y} - 0\right|} = \frac{\sum_{i}^{n}\sum_{j}^{n}\left|y_i - y_j\right|}{2n(n-1)\bar{y}} \tag{10}$$

where y_i is the attribute of individual i, n the population size, and $\bar{y}$ the average attribute.

An advantage of the Gini coefficient over some other inequality measures like variance or the Theil index is that it is bounded between 0 and 1, with 0 indicating perfect equality and 1 perfect inequality, so that it is easy to assess the severity of inequality. However, when the individual attribute is health, there is a limit on how much one person can possibly accumulate. For example, an individual's AAD cannot be too far above 100 years, and his RePLY and RCPLY, by construction, must not be bigger than one. If one makes inference on a population's AAD, RePLY or RCPLY distribution based on the 0-1 scale of the Gini coefficient, it is easy to grossly understate the true level of health inequality, because the range of *attainable inequality* is in fact much narrower.

Wagstaff (2005) suggests the solution of using the maximal value of the total pair-wise difference conditional on the mean and the boundary values for standardization.[18] Erreygers (2009a), however, recently argues for using the maximal value of the total pair-wise difference conditional on the boundary values *only* for standardization. To understand the difference between the normal Gini coefficient (G), Wagestaff's standardized Gini coefficient (W), and Erreygers' one (E), let's consider the following example. Suppose the distribution of health as measured by RCPLY in a population of six people is given by {0.4, 0.4, 0.6, 0.8, 1, 1}, so average RCPLY = 0.7, the total pair-wise difference = 5, and G = 0.238. Conditional on average RCPLY = 0.7 and the 0-1 boundaries of RCPLY, the most unequal distribution of RCPLY for the population is given by {0, 0.2, 1, 1, 1, 1}, which has a total sum of pair-wise differences equal to 7.4. Therefore, W = 5/7.4 = 0.676. On the other hand, if conditioning on only the 0-1 boundaries of RCPLY but not the mean, the maximal sum of pair-wise

[18] Both Wagstaff's and Erreygers's articles focus on the concentration index. But the arguments clearly can be equally applied to the Gini coefficient.

differences is achieved with the distribution {0, 0, 0, 1, 1, 1}, which is equal to 9. Therefore, E = 5/9 = 0.556.

Both methods could produce results that may *appear* to be counter-intuitive. For instance, the following two distributions of RCPLY: {0, 1, 1, 1, 1, 1} and {0, 0, 0, 0, 0, 1} have exactly the same E = 5/9 = 0.556 as in the previous example, although in the last distribution one person has everything and all others have nothing. On the other hand, in the following three distributions of RCPLY: {0, 1, 1, 1, 1, 1}, {0.3, 1, 1, 1, 1, 1}, {0.999, 1, 1, 1, 1, 1}, all have W = 1, despite the fact that last distribution is already very close to perfect equality. W is always equal to 1 in this case because when everyone else in the population has attained the maximal health, having one left behind is as unequal as it can get (there is no other way to distribute the total available health to make the distribution more unequal). Also, when everyone has attained the maximal (or minimal) health level, strictly speaking W is undefined despite perfect equality.

The debate between the two standardization methods has just begun, see Wagstaff (2009) and Erreygers (2009b), so it is impossible to say which method is currently preferred. In this paper, we focus on the results of W for both theoretical and empirical reasons.[19] Theoretically, a key difference between W and E is that the former is level dependent and the latter is not. That is, if the health level of everyone in the population changes by the same absolute amount while the boundaries remain intact, the value of W will alter but not that of E. We do not consider, however, level independency a necessary or even desirable property for a health inequality indicator. Empirically, we found that as far as this paper is concerned, both G and E are highly correlated to each average health measure, while W is not. Therefore, using W as an inequality measure can provides extra information about the health distribution distinct from the average health measure.

6. Data

[19] Results for G and E can be obtained from authors on request.

The proposed method is applied to year 2000 life tables of 167 countries compiled by the World Health Organization[20]. The sample coverage is constrained by the limitation of GDP per capita data. Data on real GDP per capita (PPP, constant year 2000 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. 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 exclusion 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 a population to the same age-sex specific mortality rate profiles as observed in the year of survey until the demographic structure becomes static. 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.[21]

6. Empirical Results

The summary statistics of various indicators are reported in Table 2 and the full results can be founded in Appendix 2. It can be seen that there are huge differences in income across the 167 countries, with the richest (Luxembourg) being almost eight times that of the poorest (Tanzania), and the coefficient of variation (CV) being slightly above one, indicating that

[20] The WHO constantly revises the data. The data used in the current paper is the 2007 version.
[21] 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.

there is large gap in resources available between countries. National average RCPLY is, on average, larger than national RePLY by about 10 percent. Figure 4 is a plot of average RePLY and average RCPLY against average AAD, which is equal to life expectancy at birth. It can be seen that average RePLY is of an almost perfect linear relationship with life expectancy,[22] indicating that using RePLY to measure average health status of a country is qualitatively equivalent to using life expectancy. On the contrary, average RCPLY displays a very different pattern with average AAD. In particularly, every country's average RCPLY is bigger than its average RePLY. This is expected because when a country is benchmarked against only the local frontier countries with similar income levels rather than with the global frontier countries, it is bound to 'perform' better. As expected, life expectancy is positively related to income level. Therefore, countries at the high end of the life expectancy spectrum are mostly OECD countries and those at the low end are mostly Sub-Sahara African countries. For countries with very high life expectancy, the differences between the two measures are relatively small. However, the difference between the two measures, in general widens as average RePLY falls. In percentage terms, the change for Malawi is the biggest,[23] with its average RCPLY 74% higher than its average RePLY, 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.

A comparison between RCPLY and RePLY can indicate how much of the potential health improvement can come from increasing the available resources and improving performance given the available resources. Figure 5 shows the average RePLY for each age group of Russian males, and the average RePLY that would have occurred if they were on their local frontier at each age-sex group. The gap between the top (when average RePLY = 1) and the curve of average RePLY shows how much potential improvement can be made by

[22] This is a result of the mathematics underlying the two indicators, for proof see Tang, Petrie & Rao (2006).
[23] The percentage change of Malawi is even bigger than the 1.72 of Tanzania, though Malawi is also a poor country.

providing more resources as well as increasing the efficiency of utilizing the resources. The gap between the two RePLY curves therefore indicates how much improvement can be made by closing the performance gap with its peers with existing total resources. The graph thus shows that, the poor health performance of Russian boys is more to do with the lack of resources than the lack of performance, but the opposite is true for higher aged groups. Figure 6 provides another view of the relative importance of the two ways to improve health in Russia as well as China. For any specific age group, the figure on the y-axis corresponds to the ratio of AB/OC in Figure 2. For Russia, overall improving performance can play a much bigger role than increasing total resources in improving the country's average health status. In comparison, for most Chinese age groups, improving performance plays a relatively smaller role than increasing resources, reflecting the country's already high performance but yet low income level.

In terms of health inequality Figure 7 is a scatter plot of W(AAD), W(RePLY), and W(RCPLY) against life expectancy. Here W(AAD) is computed assuming the maximal age is equal to 102.86, which is the maximum average lifespan for males and females that reach the 100 years age bracket for the year 2000. Controlling for avoidable mortality risks has a big impact on the inequality measure in that inequalities measured by W(RePLY) and W(RCPLY) are substantially larger than W(AAD) for every country. Furthermore, according to W(RePLY) and W(RCPLY), countries with higher life expectancy do not necessarily have lower health inequality, as suggested by W(AAD). This is because, by mixing avoidable and unavoidable mortality risks, AAD overstates the maximum inter-individual differences possible conditional on the mean health status. Using AAD suggests that the most unequal health distribution is where one group all reach 102.86 years of life and the rest receive zero years of life, though many individuals may die from an unavoidable death before reaching this maximal age.

Controlling for resources also has a big impact on the inequality measure as well, as indicated in Figure 8, which is scatter plot of W(RCPLY) against W(RePLY). For most countries the most unequal distribution of RePLY possible conditional on the mean is overestimated, because given the countries resources they would not be able to achieve this maximal unequal distribution.

Figure 9 is a scatter plot of W(RCPLY) against average RCPLY. It shows that there is no clear pattern between average health status and health inequality as measured by RCPLY, implying that both mean and distributional measures are important in describing the health status of a population. In particular, it can be seen that even for countries with RCPLY close to the maximal value, health inequality can still be very high. This is because, for these countries, even though most deaths are unavoidable, they can still achieve close to the most unequal distribution possible given their average health status. That is, for high income countries, even though the distribution of their RCPLY are more even (as measured by normal Gini coefficient), the standard against which their distribution is assessed is also higher, so that the inequality as measured by the standardized Gini coefficient may remain very high.

7. Relationships between the average health status and health inequality measures with other factors

In Table 3 we explore the relationship between the three average health status measures and their associated standardized Gini coefficients with other health and social factors. Two linear regression models are explored using the average health status and standardized Gini coefficients as dependent variables for each model. Model 1 includes the following explanatory variables; natural log of GDP, the percentage of GDP spent on health expenditure, the percentage of health expenditure from private expenditure, the average of the percentage of the population with access to improved sanitation and clean water, the average of the percentage of the population who have been immunized against DPT and measles, the ratio of females to males in secondary education, the average of the ethnic and language fractionalization index (where 0 is for one homogenous group and 1 is a completely heterogeneous group) and the religious fractionalization index (Alesina et al., 2003). In addition to the explanatory variables in Model 1, Model 2 also includes the Gini coefficient for income which significantly reduces the available sample size.

In terms of the results, of particular interest, is the fact that there is a negative relationship between RCPLY and income inequality and also negative relationship between health inequality as measured by W(RCPLY) and income inequality. Normally we would expect that income inequality would increase health inequality but in this case because the life tables are only grouped by age and gender, income-related health inequality would only show up in terms of a lower average health status (inefficient allocation of resources within age-sex groups) and not in the health inequality measure reported. Also of particular interest is the significance of the negative relationship between religious fractionalization and both average health status and health inequality as measured by RCPLY. While the negative relationship between religious fractionalization and average health status may be expected given discrimination between different religions within each age-sex group, the negative relationship between religious fractionalization and health inequality suggests the more heterogeneous in religious beliefs the lower health inequalities between the age-sex groups.

8. 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 a "classic" indicator, age-at-death, which resulted in the development of age-at-avoidable-death. The methodology 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 and complexities are controlled for. From AAD to age-at-avoidable-death, we considered the differences between avoidable and unavoidable deaths and examined the inequalities in the age-at-avoidable-deaths; from age-at-avoidable-death to RePLY, we have controlled for the differences between avoidable and unavoidable deaths by combining both in a single measure; from RePLY to RCPLY, we have controlled for the differences in available resources across countries. An important merit of the RCPLY measures is that it provides a method to consider the performance of a country against another while controlling for country specific factors which may affect performance.

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.

This research can be extended in a number of ways. First of all, moving from DEA to stochastic frontier analysis (SFA) is a natural extension that can take into account noise in the data, though SFA also adds additional complexities that need to be taken into account, such as, the choice of an appropriate functional form. Secondly, in the current paper we only control for income, but do not consider the allocation of resources for specific purposes, such as health expenditure, education expenditure, and social protection. Incorporating health expenditure as a measure of resources and re-estimating the frontier will provide additional information in terms of whether inequalities result from insufficient resources (GDP) being allocated to the health system, or from the low efficiency of the health system.

Reference

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., Wacziarg, R. 2003 'Fractionalization' Journal of Economic Growth, vol 8, pp. 155-194.

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.

Erreygers, G, 2009. Correcting the Concentration Index. *Journal of Health Economics*, vol 28, no. 2, pp. 504-515.

Erreygers, G, 2009b. Correcting the Concentration Index: A Reply to Wagstaff. *Journal of Health Economics*, vol 28, no. 2, pp. 521-524.

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

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.

Petrie, D, and Tang, KK "A Rethink on Measuring Health Inequalities Using the Gini Coefficient" *School of Economic Discussion Paper, University of Queensland* No.381, 2008

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.

Wagstaff , A, 2005. The bounds of the concentration index when the variable of interest is binary, with an application to immunization inequality. *Health Economics*, 14: 429-432.

Wagstaff , A, 2009. Correcting the concentration index: A comment. *Journal of Health Economics*, , vol 28, no. 2, pp. 516-520 .

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		Countries of the lowest mortality risks after controlling for income	
age	**Male**	**Female**	**Male**	**Female**
0	Singapore	Iceland	Tanzania, Yemen, Viet Nam, Moldova, Jamaica, Belarus, Croatia, Slovenia, Czech Republic, Singapore	Tanzania, Vietnam, Moldova, Belarus, Slovenia, Czech Republic, Singapore, Iceland
1	Sweden	Sweden	Tanzania, Yemen, Viet Nam, Moldova, Georgia, Dominica, TFYR Macedonia, Costa Rica, Chile, Croatia, Poland, Czech Republic, Greece, Singapore, Spain, Ireland, Finland, Sweden	Tanzania, Yemen, Viet Nam, Moldova, Armenia , Georgia, Croatia, Poland, Slovakia, Slovenia, Czech Republic, Malta, Seychelles, Greece, Cyprus, Spain, Finland, Australia, Sweden
5	Singapore	Slovenia	Tanzania, Yemen, Tajikistan, Armenia, Belarus, Costa Rica, Chile, Croatia, Poland, Slovakia, Hungary, Slovenia, Malta, Greece, Cyprus, New Zealand, Singapore	Tanzania, Yemen, Tajikistan, Uzbekistan, Kyrgyzstan, Moldova, Georgia , Belarus, TFYR Macedonia, Costa Rica, Chile, Mauritius, Croatia, Poland, Uruguay, Lithuania , Hungary, Slovenia
10	Iceland	Luxembourg	Tanzania, Yemen, Tajikistan, Uzbekistan, Viet Nam, Moldova, Armenia, Georgia, Jamaica, Belarus, Saint Vincent and Grenadines, TFYR Macedonia, Bulgaria, Costa Rica, Estonia, Chile, Croatia, Poland, Uruguay, Lithuania, Hungary, Czech Republic, Malta, Greece, Cyprus, Spain, Ireland, Israel, Finland, Australia, Sweden, Germany, France, Iceland	Tanzania, Yemen, Tajikistan, Mongolia, Uzbekistan, Kyrgyzstan, Moldova , Armenia, TFYR Macedonia, Bulgaria, Chile, Croatia, Poland, Uruguay, Lithuania, Slovakia, Hungary, Republic of Korea, Slovenia, Czech Republic, Greece, Portugal, Cyprus, Singapore, Spain, Ireland, Israel, Kuwait, Finland, Australia, Sweden, Italy, Germany, France , UK, Canada, Belgium, Iceland, Netherlands, Japan, Austria, Denmark, Norway, Switzerland, USA, Luxembourg
15	Singapore	Luxembourg	Tanzania, Mozambique, Mali, Niger, Yemen, Madagascar, Uzbekistan, Moldova, Armenia, Georgia, Malta, Singapore	Tanzania, Yemen, Mongolia, Armenia, Croatia, Poland, Hungary , Slovenia, Greece, Singapore, Spain, Israel, Sweden, Italy, France, Netherlands, Japan, Switzerland, Luxembourg
20	United Arab Emirates	Malta	Tanzania, Yemen, Armenia, Malta, United Arab Emirates	Tanzania, Yemen, Mongolia, Moldova, Armenia , Dominica, Croatia, Poland, Slovakia, Malta
25	Singapore	Malta	Tanzania, Yemen, Viet Nam, Armenia, Singapore	Tanzania, Yemen, Tajikistan, Viet Nam, Armenia , TFYR Macedonia, Poland, Hungary, Slovenia, Malta
30	Malta	Sweden	Tanzania, Yemen, Viet Nam, China, Malta	Tanzania, Yemen, Mongolia, Viet Nam, Armenia , Slovakia, Malta, Croatia, Sweden
35	Kuwait	Iceland	Tanzania, Yemen, Viet Nam, China, Albania, Kuwait	Tanzania, Yemen, Uzbekistan, Viet Nam, Armenia, Georgia, Chile , Malta, Croatia , Iceland
40	Iceland	Malta	Tanzania, Yemen, Viet Nam, China, Panama, Costa Rica, Malta, Kuwait, Iceland	Tanzania, Yemen, Viet Nam, Armenia, Malta
45	Iceland	Kuwait	Tanzania, Yemen, Viet Nam, China, Panama, Costa Rica, Malta, Kuwait, Iceland	Tanzania, Yemen, Viet Nam, Armenia, Panama, Malta, Greece, Kuwait
50	Iceland	Spain	Tanzania, Yemen, Viet Nam, China, Panama, Costa Rica, Malta, Kuwait, Iceland	Tanzania, Yemen, Viet Nam, Armenia, Georgia, Albania, Panama , Bahrain, Malta, Greece, Spain
55	Australia	Cyprus	Tanzania, Yemen, Mongolia, Viet Nam, Panama, Australia	Tanzania, Yemen, Mongolia, Viet Nam, Albania, Cyprus
60	Iceland	Japan	Tanzania, Yemen, Viet Nam, Nicaragua, Panama, Iceland	Tanzania, Yemen, Viet Nam, Panama, Greece, Spain, Japan
65	Iceland	Japan	Tanzania, Yemen, Dominica, Iceland	Tanzania, Viet Nam, Panama, Spain, Japan
70	Japan	Japan	Tanzania, Yemen, Panama, Japan	Tanzania, Tajikistan, Panama, Japan
75	Japan	Japan	Tanzania, Mongolia, Nicaragua, Mexico, Japan	Tanzania, Tajikistan, Panama, Japan
80	Mexico	Japan	Tanzania, Mongolia, Mexico	Tanzania, Tajikistan, Japan
85	Mexico	Japan	Tanzania, Mongolia, Mexico	Tanzania, Tajikistan, Japan
90	Malaysia	Japan	Tanzania, Mongolia, Malaysia	Tanzania, Tajikistan, Seychelles, Japan
95	Malaysia	Malaysia	Tanzania, Mongolia, Malaysia	Tanzania, Tajikistan, Malaysia

Note: When there is more than one country, countries are listed according to their income level, from the lowest to the highest.

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

	GDP per capita	Average AAD	Average RePLY	Average RCPLY	W(AAD)[b]	W(RePLY)	W(RCPLY)
Mean	7494	62.52	0.80	0.88	0.46	0.82	0.88
Std dev	7938	11.67	0.14	0.10	0.09	0.05	0.06
CV[a]	1.06	0.19	0.18	0.11	0.20	0.06	0.07
Max	38045	78.94	0.99	1	0.70	0.98	0.98
Mini	498	31.11	0.41	0.53	0.32	0.63	0.67

a. CV = coefficient of variation.

b. W = Wagstaff's standardized Gini coefficient.

Table 3 Regression results for national average health status measures and health inequality measures

	Average AAD (LE)		Average RePLY		Average RCPLY		W(AAD)[b]		W(RePLY)		W(RCPLY)	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	13.54	17.26	0.219*	0.263	0.807***	0.940***	0.846***	0.783***	0.692***	0.685***	1.113***	1.112***
	(9.863)	(13.10)	(0.120)	(0.160)	(0.127)	(0.147)	(0.0628)	(0.0823)	(0.0620)	(0.0883)	(0.0717)	(0.0974)
ln(gdp)	4.478***	4.683***	0.0521***	0.0545***	-0.0027	-0.00366	-0.237***	-0.0195**	0.0330***	0.0378***	-0.0131*	-0.00852
	(0.879)	(1.282)	(0.0107)	(0.0156)	(0.0107)	(0.0152)	(0.00610)	(0.00859)	(0.00691)	(0.0103)	(0.00767)	(0.0113)
Health Expenditure (%GDP)	1.678	26.93	-0.0406	0.281	0.355	0.626	0.249*	-0.0136	0.7093***	0.513	0.703***	0.520
	(23.65)	(41.19)	(0.288)	(0.499)	(0.301)	(0.541)	(0.143)	(0.247)	(0.1937)	(0.330)	(0.217)	(0.364)
Private (% Health Expenditure)	0.0337	0.0572	0.000418	0.00070	0.000196	0.000460	-0.000155	-0.000207	0.000187	0.000365	0.000249	0.000503
	(0.0285)	(0.0349)	(0.000350)	(0.000428)	(0.000366)	(0.000446)	(0.000223)	(0.000281)	(0.000207)	(0.000311)	(0.000237)	(0.000332)
Sanitation & Water Access	0.175***	0.173***	0.00215***	0.00213***	0.00205**	0.00192**	-0.00151***	-0.00152***	-0.000311	-0.000264	-8.01e-6	0.0000654
	(0.0587)	(0.0625)	(0.000713)	(0.000761)	(0.000791)	(0.000749)	(0.000362)	(0.000406)	(0.000380)	(0.000465)	(0.000419)	(0.000500)
Immunization	0.0029	-0.0970	0.0000866	-0.00112	0.000085	-0.00145	-0.000976**	-0.000697	-0.00116***	-0.00173***	-0.00105**	-0.00194***
	(0.0650)	(0.0787)	(0.000797)	(0.000960)	(0.000875)	(0.000999)	(0.000423)	(0.000455)	(0.000380)	(0.000589)	(0.000444)	(0.000647)
Ratio of females to males in Secondary Education	0.0337	0.157**	0.0004561	0.00196**	-0.000350	0.00130	-0.000385	-0.000719	-0.000577	-0.000105	-0.000471	0.000429
	(0.0636)	(0.0718)	(0.000774)	(0.000874)	(0.000904)	(0.000963)	(0.000403)	(0.000491)	(0.000378)	(0.000551)	(0.000458)	(0.000623)
Ethnic and Language Fractionalization	-7.947***	-2.136	-0.0975***	-0.250	-0.0831**	-0.0245	0.0683***	0.0432	-0.00802	-0.00255	-0.0226	-0.00431
	(3.023)	(4.606)	(0.0368)	(0.0562)	(0.0372)	(0.0545)	(0.0187)	(0.0293)	(0.0205)	(0.0284)	(0.0237)	(0.0318)
Religious Fractionalization	-6.621***	-11.42***	-0.0798***	-0.0139***	-0.0636**	-0.121***	0.00519	0.0187	-0.0583***	-0.0813***	-0.0692***	-0.103***
	(1.903)	(2.664)	(0.0232)	(0.0325)	(0.0246)	(0.0346)	(0.0130)	(0.0167)	(0.0157)	(0.0216)	(0.0180)	(0.0247)
Income Inequality (Gini)	-	-0.278***	-	-0.00338***	-	-0.00422***	-	0.00143***	-	-0.000656	-	-0.00129*
		(0.0836)		(0.00101)		(0.00106)		(0.000430)		(0.000638)		(0.000727)
R-squared	0.77	0.77	0.77	0.77	0.45	0.54	0.85	0.85	0.39	0.36	0.32	0.39
Sample Size	140	92	140	92	140	92	140	92	140	92	140	92

***, **,* denote significance at the 1, 5, 10% level respectively. Robust standard errors reported in parentheses.

Tanzania dropped from all regressions for consistency because W(RCPLY) Tanzania not defined. Ethnic and language fractionalization taken as the average of these two measures from Alesina et al. (2003) which are highly correlated. Sanitation & water access is the average of these two measures from the WHO database where the missing values of sanitation have been imputed from a linear regression using water access and a constant as explanatory variables. Income Gini coefficient data from the World Development Indicators (WDI). All explanatory variables are taken as the average of all available data from 1990 to 1999.

Figure 1 Constructing the Global and Local Frontiers of Mortality Rates

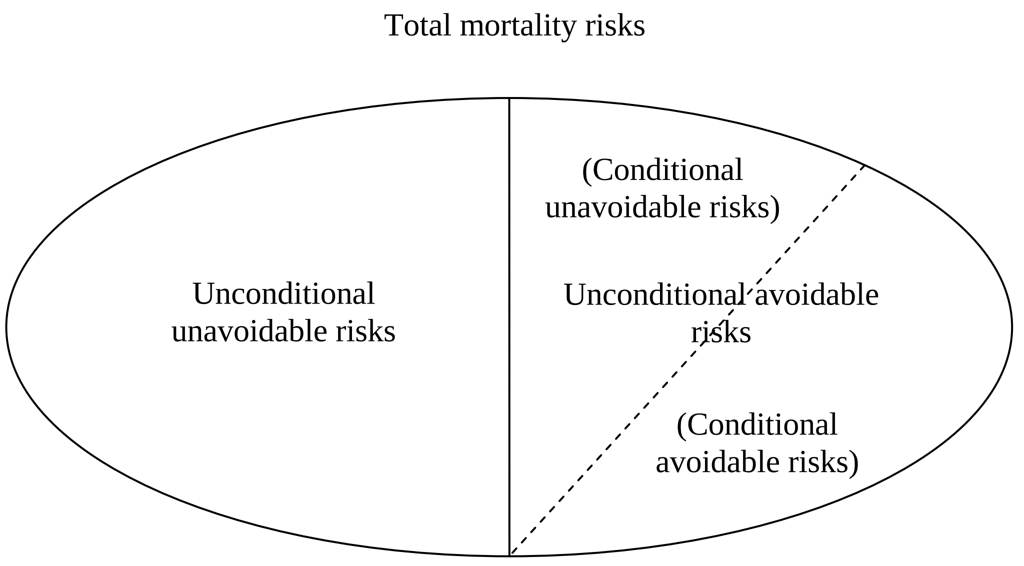


Figure 2 Constructing the Global and Local Frontiers of Mortality Rates

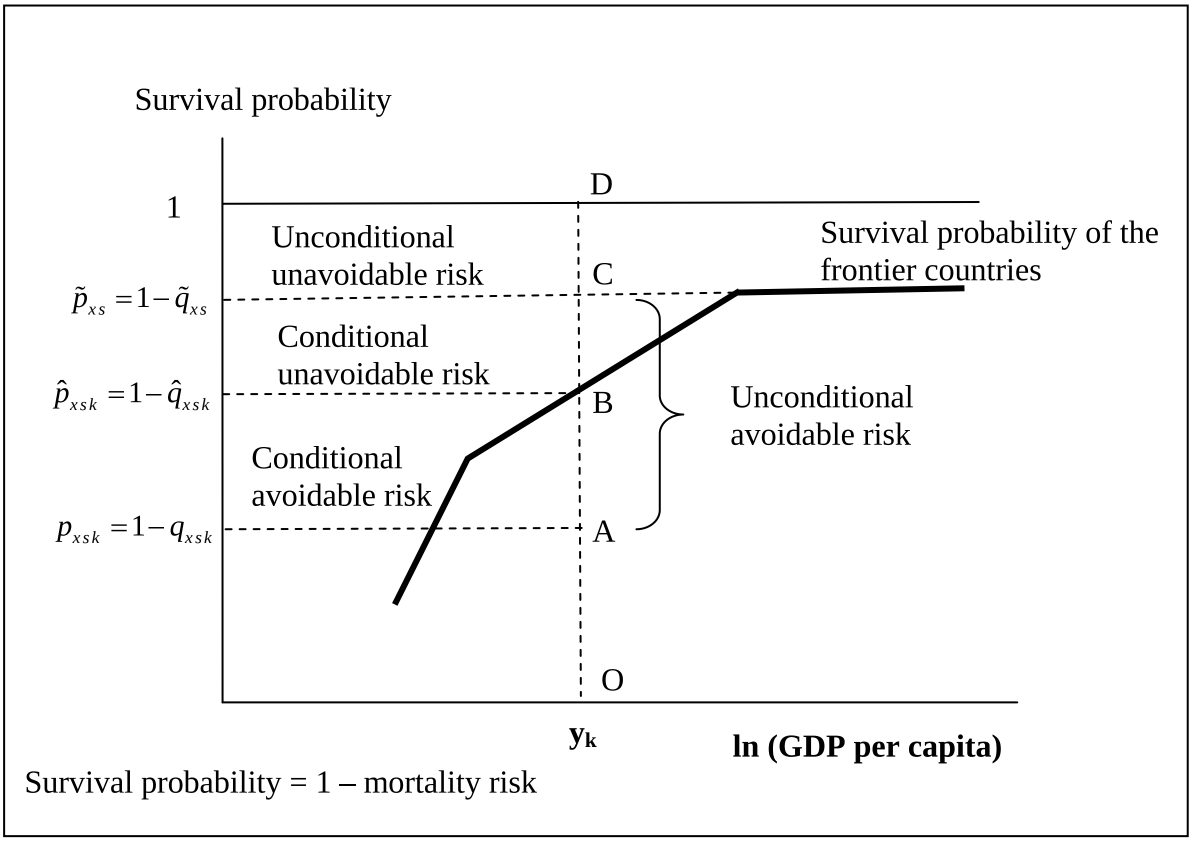


Figure 3 The frontier of survival probability for males aged 75

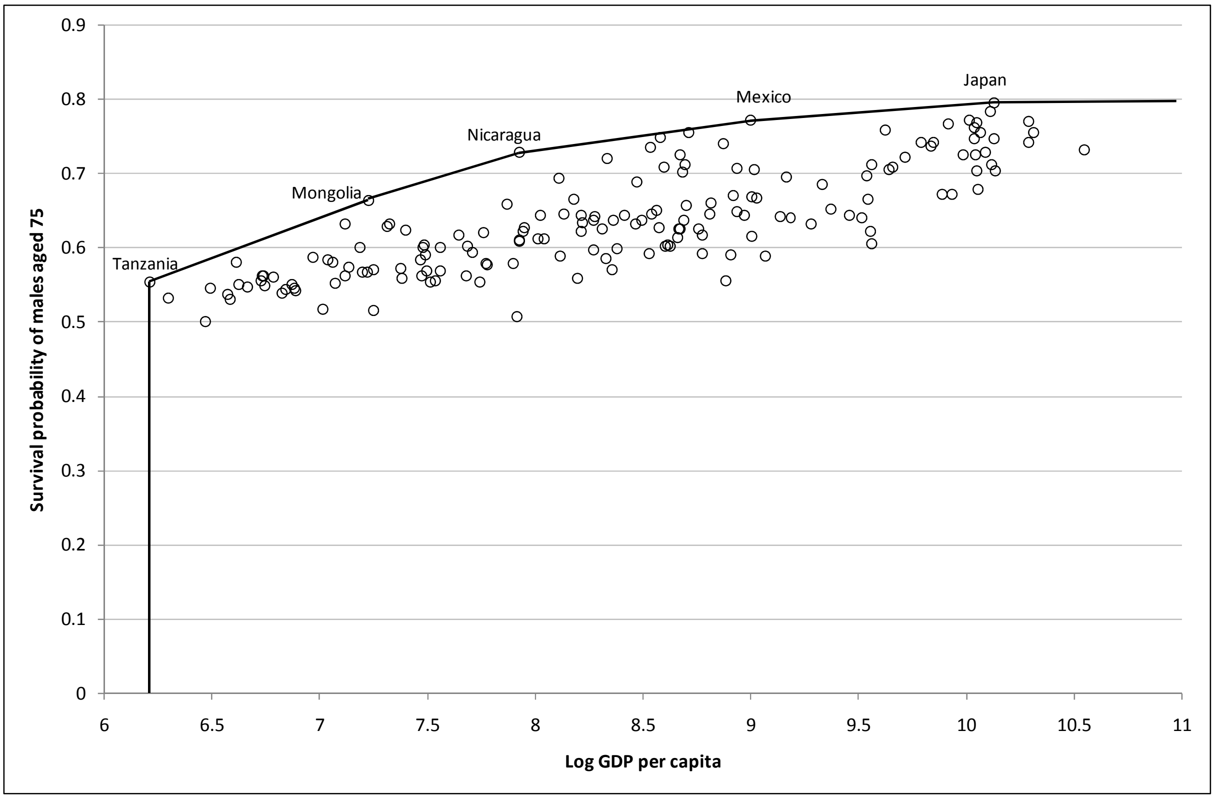


Figure 4 National averages of RCPLY and RePLY against life expectancy at birth

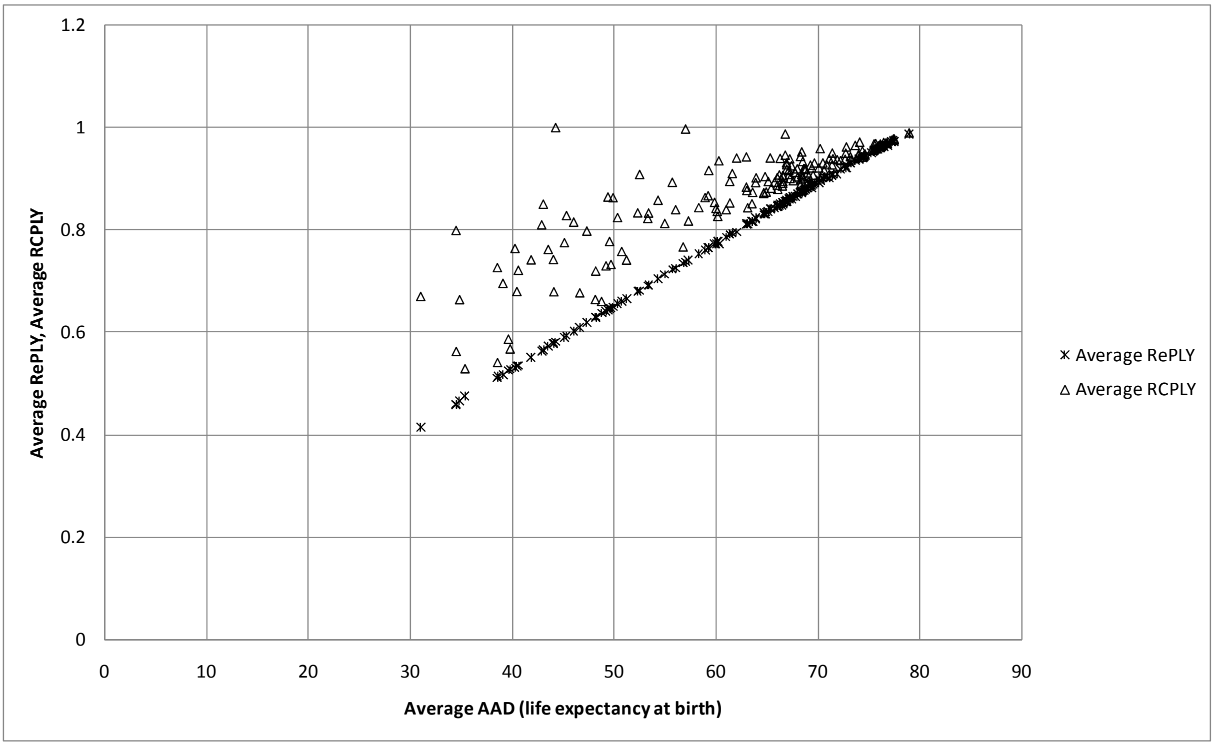


Figure 5 Average RePLY of individual age groups for Russia and its peer country (males)

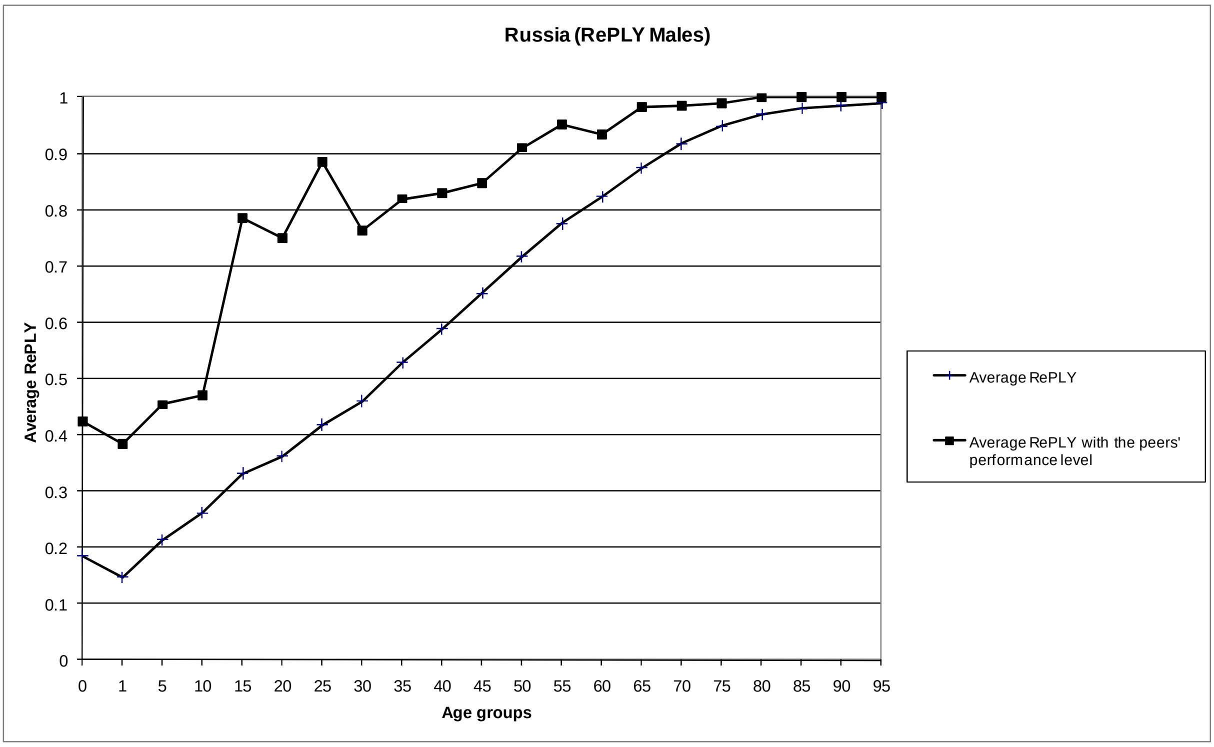


Figure 6 Potential improvement by increasing performance conditional on current total resources, Russia and China

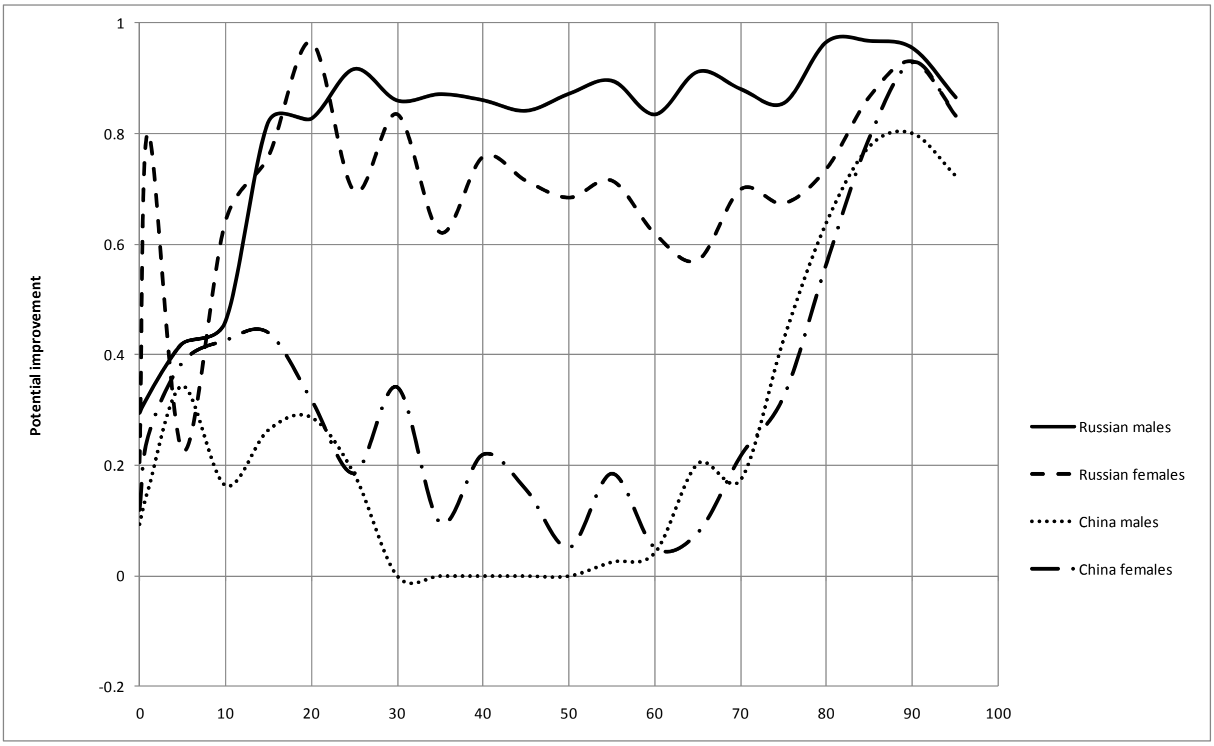


Figure 7 Standardized Gini coefficients against life expectancy

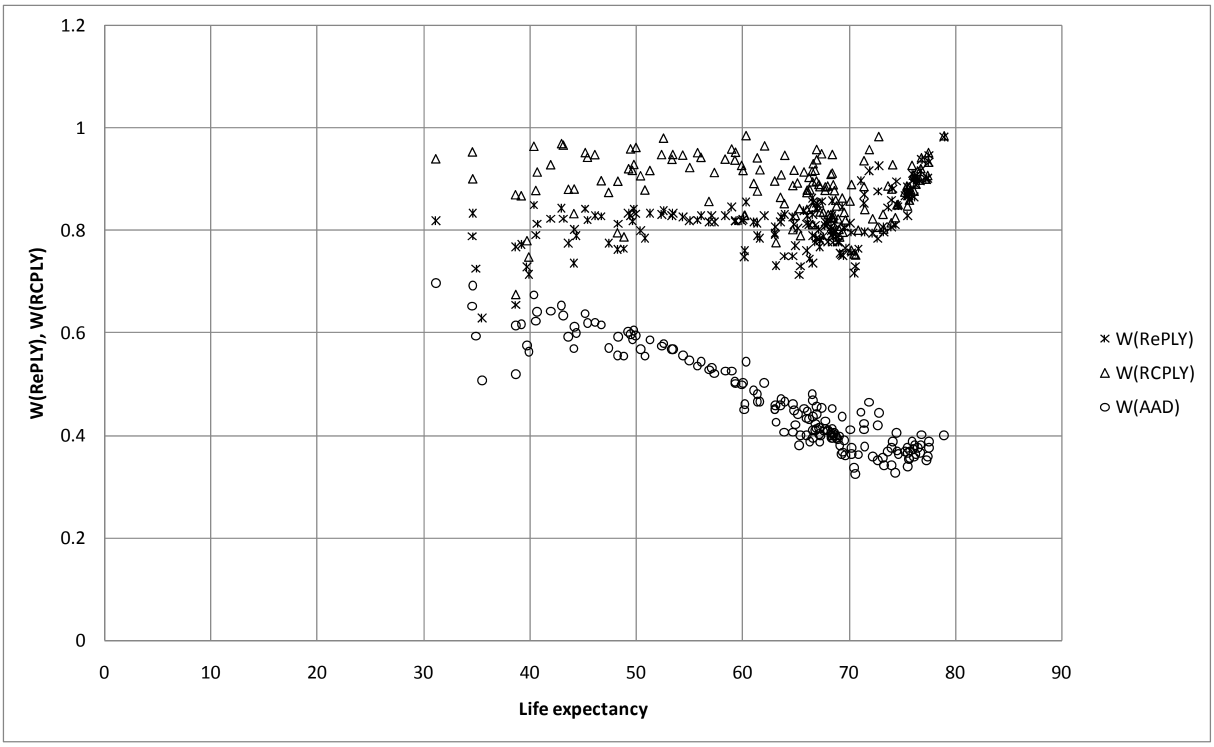


Figure 8 Standardized Gini coefficients of RCPLY and RePLY

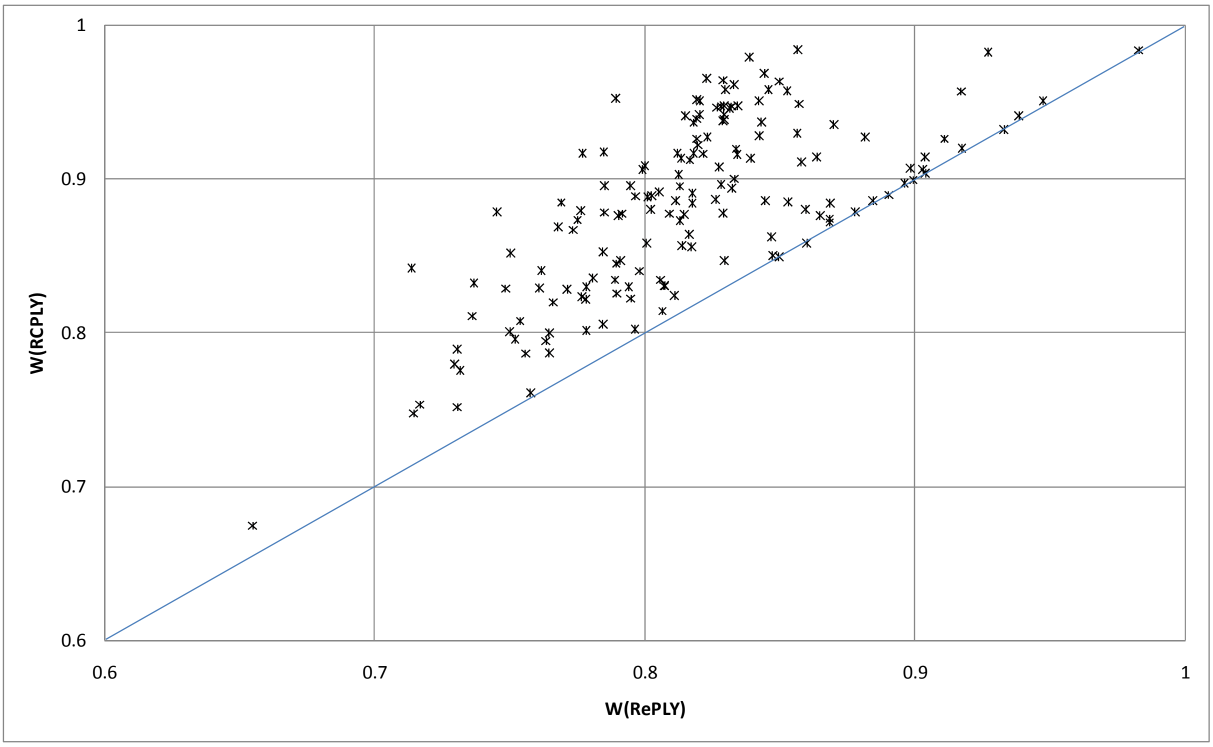
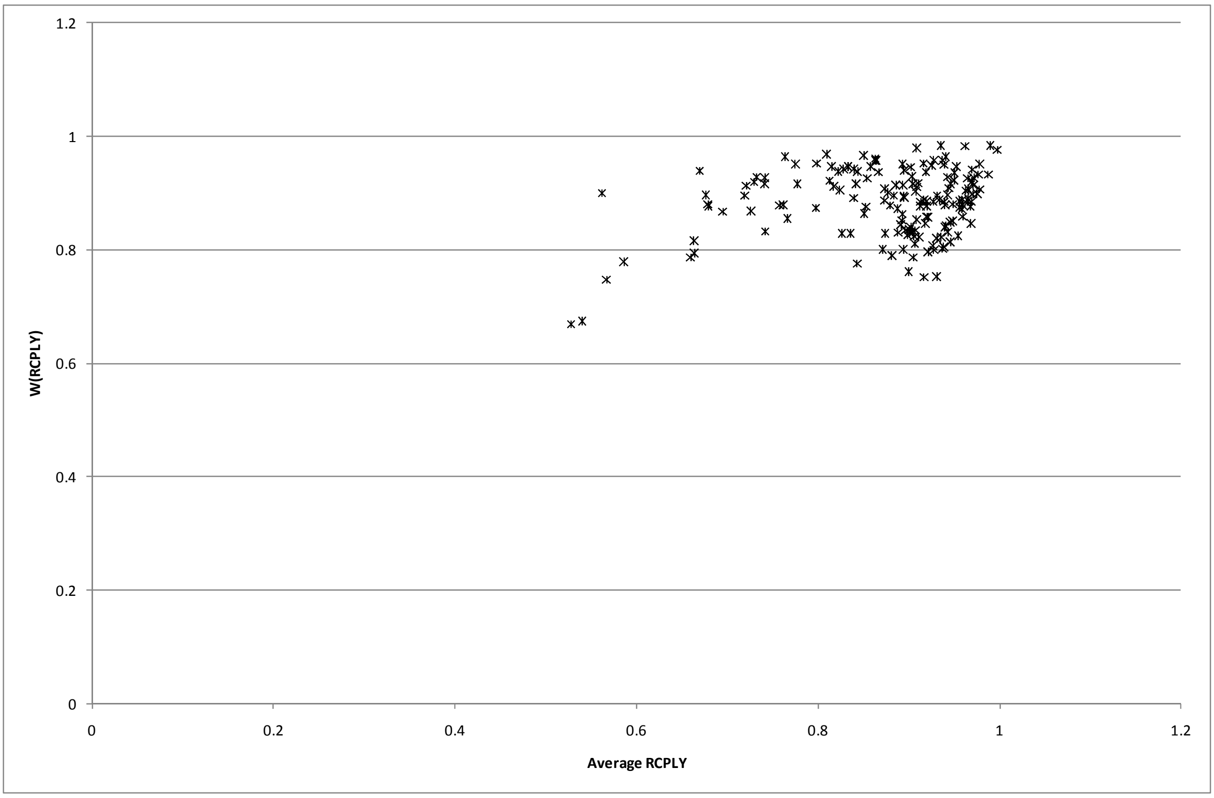


Figure 9 Standardized Gini coefficient of RCPLY and average RCPLY



Appendix Full Estimation Results

Country	Income	ADD	W(ADD)	RePLY	W(RePLY)	RCPLY	W(RCPLY)
Albania	2728	67.25	0.39	0.86	0.77	0.94	0.88
Algeria	5113	66.58	0.44	0.85	0.83	0.89	0.89
Angola	1408	34.59	0.69	0.46	0.83	0.56	0.90
Antigua and Barbuda	9296	68.50	0.39	0.88	0.79	0.90	0.83
Argentina	11310	71.41	0.41	0.91	0.85	0.93	0.88
Armenia	2088	66.80	0.41	0.86	0.78	0.95	0.92
Australia	22285	77.48	0.39	0.97	0.95	0.98	0.95
Austria	25067	76.17	0.38	0.96	0.90	0.96	0.90
Azerbaijan	2762	60.03	0.50	0.77	0.82	0.84	0.92
Bahamas	15671	69.35	0.44	0.88	0.85	0.89	0.86
Bahrain	14218	70.62	0.32	0.90	0.73	0.92	0.75
Bangladesh	1321	59.32	0.50	0.77	0.82	0.92	0.95
Belarus	4346	66.58	0.39	0.85	0.74	0.91	0.81
Belgium	24050	75.44	0.38	0.95	0.88	0.96	0.89
Belize	4883	67.74	0.41	0.87	0.81	0.91	0.88
Benin	884	49.95	0.60	0.65	0.83	0.86	0.96
Bolivia	2227	59.89	0.50	0.77	0.82	0.85	0.93
Botswana	6357	38.64	0.52	0.51	0.65	0.54	0.67
Brazil	6746	66.07	0.45	0.85	0.83	0.88	0.88
Bulgaria	5822	69.28	0.36	0.89	0.75	0.93	0.81
Burkina Faso	935	40.67	0.64	0.54	0.81	0.72	0.91
Burundi	783	38.62	0.61	0.51	0.77	0.73	0.87
Cambodia	1409	53.34	0.57	0.69	0.83	0.82	0.94
Cameroon	1803	48.24	0.59	0.63	0.81	0.72	0.90
Canada	23528	76.76	0.38	0.97	0.92	0.97	0.92
Cape Verde	3682	66.23	0.43	0.85	0.81	0.91	0.90
Central African Republic	1179	40.53	0.62	0.53	0.79	0.68	0.88
Chad	850	46.08	0.62	0.60	0.83	0.81	0.95
Chile	7606	73.66	0.37	0.94	0.84	0.97	0.89
China	2608	68.43	0.41	0.88	0.83	0.95	0.95
Colombia	5963	68.42	0.45	0.87	0.86	0.91	0.91
Comoros	1789	59.26	0.50	0.77	0.82	0.87	0.94
Congo	1137	50.38	0.57	0.66	0.80	0.82	0.91
Costa Rica	7114	74.10	0.39	0.94	0.88	0.97	0.93
Côte d'Ivoire	1601	44.14	0.61	0.58	0.80	0.68	0.88
Croatia	8136	70.49	0.34	0.90	0.72	0.93	0.75
Cyprus	16579	74.36	0.33	0.95	0.81	0.95	0.82
Czech Republic	13944	72.68	0.35	0.93	0.78	0.94	0.81
Dem. Rep. of the Congo	918	41.92	0.64	0.55	0.82	0.74	0.93
Denmark	25144	74.50	0.37	0.94	0.85	0.95	0.85
Djibouti	2299	46.69	0.62	0.61	0.83	0.68	0.90
Dominica	5072	71.41	0.42	0.91	0.87	0.95	0.94
Dominican Republic	5040	64.71	0.46	0.83	0.83	0.87	0.89
Ecuador	3318	67.42	0.45	0.86	0.86	0.93	0.95
Egypt	3020	63.91	0.41	0.82	0.75	0.89	0.85
El Salvador	4169	66.63	0.47	0.85	0.86	0.90	0.93
Equatorial Guinea	2163	51.26	0.59	0.67	0.83	0.74	0.92
Eritrea	1115	44.10	0.57	0.58	0.74	0.74	0.83
Estonia	7596	68.49	0.40	0.88	0.78	0.91	0.82
Ethiopia	751	45.38	0.62	0.59	0.82	0.83	0.94
Fiji	4748	67.21	0.40	0.86	0.78	0.91	0.85
Finland	21731	75.25	0.37	0.95	0.87	0.96	0.87
France	23090	76.81	0.40	0.97	0.94	0.97	0.94

Gabon	6467	56.81	0.53	0.74	0.82	0.77	0.86
Gambia	1594	56.07	0.54	0.73	0.83	0.84	0.94
Georgia	2174	66.31	0.39	0.85	0.75	0.94	0.88
Germany	22971	75.55	0.37	0.96	0.87	0.96	0.87
Ghana	1745	55.00	0.55	0.71	0.82	0.81	0.92
Greece	15076	75.67	0.35	0.96	0.87	0.97	0.88
Grenada	5759	64.70	0.41	0.83	0.75	0.87	0.80
Guatemala	3685	63.61	0.47	0.82	0.83	0.87	0.91
Guinea	1826	49.25	0.60	0.64	0.83	0.73	0.92
Guinea-Bissau	982	45.18	0.64	0.59	0.84	0.77	0.95
Guyana	3343	61.38	0.47	0.79	0.79	0.85	0.88
Haiti	1761	50.79	0.55	0.66	0.78	0.76	0.88
Honduras	2829	64.83	0.45	0.83	0.81	0.90	0.92
Hungary	10713	69.11	0.38	0.88	0.76	0.90	0.79
Iceland	24651	77.25	0.35	0.97	0.90	0.98	0.90
India	1917	58.34	0.52	0.75	0.83	0.84	0.94
Indonesia	2768	63.00	0.45	0.81	0.79	0.88	0.90
Iran (Islamic Republic of)	5282	66.04	0.43	0.85	0.81	0.89	0.87
Ireland	19634	73.97	0.34	0.94	0.81	0.95	0.81
Israel	20289	76.06	0.37	0.96	0.90	0.96	0.91
Italy	22864	76.67	0.37	0.97	0.90	0.97	0.90
Jamaica	3562	70.23	0.38	0.90	0.80	0.96	0.89
Japan	24980	78.94	0.40	0.99	0.98	0.99	0.98
Jordan	3923	68.52	0.40	0.88	0.80	0.93	0.89
Kazakhstan	4260	60.20	0.46	0.78	0.76	0.83	0.83
Kenya	1060	47.38	0.57	0.62	0.78	0.80	0.87
Kiribati	3902	61.03	0.49	0.79	0.82	0.84	0.89
Kuwait	20562	73.26	0.34	0.93	0.80	0.94	0.80
Kyrgyzstan	1636	61.62	0.46	0.79	0.78	0.91	0.92
Lao People's Dem. Republic	1233	52.36	0.57	0.68	0.83	0.83	0.95
Latvia	6710	68.04	0.41	0.87	0.78	0.90	0.83
Lebanon	3914	67.16	0.41	0.86	0.80	0.92	0.89
Lesotho	2387	39.69	0.58	0.53	0.73	0.59	0.78
Lithuania	8345	70.09	0.41	0.89	0.81	0.92	0.86
Luxembourg	38045	75.79	0.37	0.96	0.88	0.96	0.88
Madagascar	842	52.54	0.58	0.68	0.84	0.91	0.98
Malawi	543	34.56	0.65	0.46	0.79	0.80	0.95
Malaysia	7195	69.42	0.37	0.89	0.75	0.92	0.80
Mali	713	42.95	0.65	0.56	0.84	0.81	0.97
Malta	14225	75.51	0.34	0.96	0.83	0.97	0.85
Mauritania	1875	49.75	0.60	0.65	0.84	0.73	0.93
Mauritius	7848	68.96	0.39	0.88	0.78	0.91	0.82
Mexico	8080	71.91	0.46	0.91	0.92	0.94	0.96
Micronesia (Fed. States of)	6477	63.55	0.46	0.82	0.82	0.85	0.86
Mongolia	1375	62.05	0.50	0.80	0.83	0.94	0.96
Morocco	3408	66.95	0.44	0.86	0.84	0.92	0.94
Mozambique	661	43.11	0.63	0.57	0.82	0.85	0.97
Namibia	5578	48.20	0.56	0.63	0.76	0.66	0.79
Nepal	1165	55.75	0.53	0.72	0.82	0.89	0.95
Netherlands	24716	75.69	0.35	0.96	0.86	0.96	0.86
New Zealand	17866	75.93	0.39	0.96	0.91	0.96	0.93
Nicaragua	2767	66.95	0.45	0.86	0.85	0.93	0.96
Niger	723	40.34	0.67	0.53	0.85	0.76	0.96
Nigeria	844	49.44	0.60	0.64	0.83	0.86	0.96
Norway	29307	76.30	0.36	0.96	0.89	0.97	0.89
Oman	11727	69.54	0.39	0.89	0.81	0.91	0.83

Pakistan	1773	58.96	0.53	0.76	0.85	0.86	0.96
Panama	5331	72.80	0.44	0.92	0.93	0.96	0.98
Papua New Guinea	2371	57.32	0.52	0.74	0.82	0.82	0.91
Paraguay	4513	67.98	0.41	0.87	0.81	0.92	0.89
Peru	4277	65.76	0.45	0.84	0.84	0.89	0.91
Philippines	3707	65.15	0.44	0.84	0.81	0.89	0.89
Poland	8140	71.48	0.38	0.91	0.80	0.94	0.84
Portugal	15415	74.01	0.38	0.94	0.86	0.95	0.88
Republic of Korea	12771	72.22	0.36	0.92	0.79	0.94	0.82
Republic of Moldova	1921	65.33	0.38	0.84	0.71	0.94	0.84
Romania	5988	68.82	0.40	0.88	0.79	0.92	0.85
Russian Federation	7373	63.13	0.43	0.81	0.73	0.84	0.78
Rwanda	974	39.16	0.62	0.52	0.77	0.69	0.87
Saint Kitts and Nevis	9570	68.37	0.40	0.88	0.79	0.90	0.83
Saint Lucia	5412	68.74	0.40	0.88	0.80	0.92	0.86
Saint Vincent and Grenadines	4763	67.77	0.43	0.87	0.82	0.91	0.88
Samoa	4072	66.03	0.40	0.85	0.76	0.90	0.84
Sao Tome and Principe	1777	61.37	0.48	0.79	0.81	0.89	0.94
Saudi Arabia	13521	68.29	0.40	0.87	0.81	0.89	0.83
Senegal	1338	53.42	0.57	0.69	0.83	0.83	0.95
Seychelles	14074	69.05	0.40	0.88	0.78	0.89	0.80
Sierra Leone	645	31.11	0.70	0.41	0.82	0.67	0.94
Singapore	18674	76.12	0.36	0.96	0.86	0.97	0.88
Slovakia	9745	70.87	0.36	0.90	0.76	0.93	0.80
Slovenia	13840	73.19	0.36	0.93	0.81	0.94	0.83
Solomon Islands	2346	63.95	0.47	0.82	0.83	0.90	0.95
South Africa	8687	48.82	0.55	0.64	0.76	0.66	0.79
Spain	18901	76.44	0.38	0.96	0.90	0.97	0.91
Sri Lanka	2814	66.93	0.41	0.86	0.79	0.93	0.90
Sudan	1255	54.35	0.56	0.70	0.83	0.86	0.95
Suriname	5520	64.94	0.42	0.84	0.77	0.87	0.83
Swaziland	4130	39.86	0.56	0.53	0.71	0.57	0.75
Sweden	22776	77.40	0.36	0.98	0.90	0.98	0.91
Switzerland	29381	77.48	0.38	0.97	0.93	0.98	0.93
Syrian Arab Republic	3042	68.30	0.40	0.87	0.80	0.94	0.91
Tajikistan	1233	60.31	0.54	0.77	0.86	0.93	0.98
TFYR Macedonia	5812	69.66	0.36	0.89	0.77	0.93	0.82
Thailand	5834	66.52	0.48	0.85	0.86	0.89	0.91
Togo	1365	49.61	0.59	0.65	0.82	0.78	0.92
Tonga	5939	67.28	0.40	0.86	0.78	0.90	0.84
Trinidad and Tobago	7444	67.59	0.41	0.87	0.79	0.90	0.83
Tunisia	5233	68.63	0.40	0.88	0.81	0.92	0.88
Turkey	5907	66.56	0.41	0.85	0.79	0.89	0.84
Turkmenistan	3625	60.15	0.45	0.78	0.75	0.84	0.83
Uganda	965	43.59	0.59	0.57	0.78	0.76	0.88
Ukraine	5453	65.43	0.40	0.84	0.73	0.88	0.79
United Arab Emirates	23221	70.21	0.36	0.90	0.76	0.90	0.76
United Kingdom	23122	74.62	0.36	0.95	0.85	0.95	0.85
United Republic of Tanzania	498	44.32	0.60	0.58	0.79	1.00	NA
United States of America	30154	74.43	0.40	0.94	0.90	0.94	0.90
Uruguay	8229	72.73	0.42	0.92	0.88	0.95	0.92
Uzbekistan	1497	63.01	0.45	0.81	0.79	0.94	0.93
Vanuatu	3110	63.05	0.46	0.81	0.81	0.88	0.90
Venezuela	6076	71.12	0.44	0.90	0.90	0.94	0.95
Viet Nam	1516	66.81	0.42	0.86	0.81	0.99	0.93
Yemen	743	57.04	0.53	0.74	0.83	1.00	0.98

Zambia	836	34.91	0.59	0.47	0.73	0.66	0.82
Zimbabwe	2682	35.44	0.51	0.47	0.63	0.53	0.67