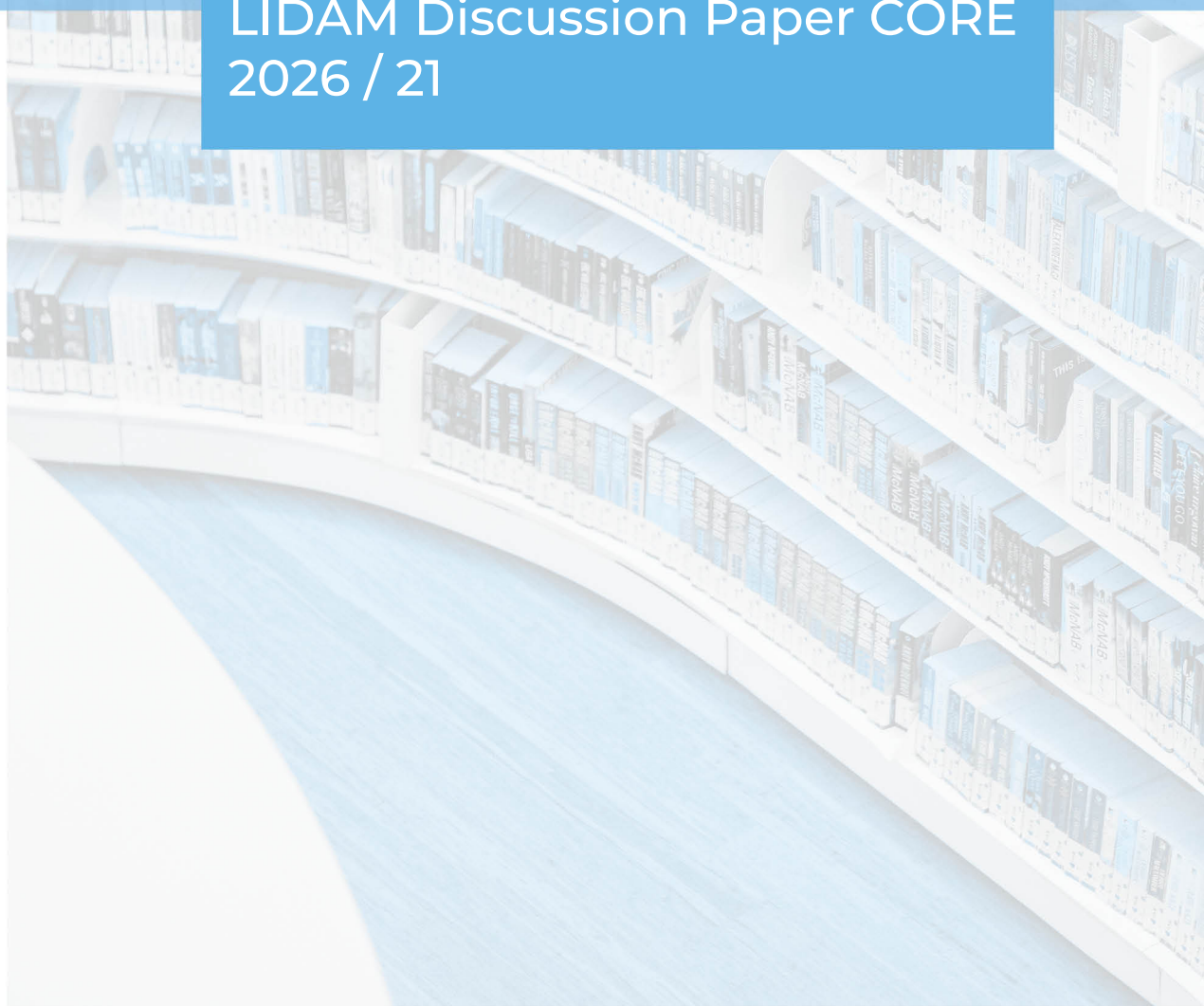
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The Invisible Continent.

Counting the Missing Poor in Developing Countries*

Mathieu Lefebvre[†], Harun Onder [‡], Pierre Pestieau[§], Gregory Ponthière[¶], Emi Suzuki[‖]

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Abstract

Because the poor face higher mortality, they are under-represented in the samples used to measure poverty. This paper quantifies this *missing poor* bias across 92 developing and least developed countries by comparing observed headcount poverty rates with counterfactual rates that would prevail if all individuals enjoyed the survival conditions of the top income class. Using income distributions and life expectancy by wealth quintile, we find the bias to be substantial and highly heterogeneous, from negligible in parts of Central Asia to 15 percentage points in Bolivia and 36 in Bhutan. Aggregated, the correction reveals an invisible continent of more than 116 million uncounted poor, large enough to reverse international poverty rankings. Instrumenting health system coverage with malaria ecology, we then show that universal health coverage causally reduces both the bias and the steepness of the income-mortality gradient through which it arises. A ten point gain in coverage lowers the bias by about one percentage point, three times the OLS estimate. Progress toward universal health coverage therefore yields a second dividend, correcting a measurement distortion concentrated where deprivation is deepest.

Keywords: poverty, measurement, mortality, missing poor bias.

JEL classification codes: I32, J11, J17.

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[†]University of Strasbourg, BETA, CNRS, Strasbourg, France, mathieu.lefebvre@unistra.fr

[‡]Texas A&M University, College Station, TX, USA, harun.onder@ag.tamu.edu

[§]University of Liège, CORE and TSE, Belgium, ppestieau@uliege.be

[¶]ENS-Rennes, CREM, Frace, gregory.ponthiere@ens-rennes.fr

[‖]Development Data Group, World Bank, Washington, DC, USA, esuzuki1@worldbank.org

1 Introduction

A major contribution of economics was to demonstrate that markets can, thanks to the informational value of market prices ('price signals'), coordinate the productive forces of the society. This point was made by Adam Smith (1776) by means of his well-known Invisible Hand metaphor. But it is less well-known that the 'coordination' by market forces can, under some circumstances, take terrible forms. According to Smith's theory of the natural wage (equal to the subsistence wage), a low demand for labor implies, in a pure market economy (without regulation or social insurance), that the market wage falls *below the subsistence wage*, i.e., the wage required for the reproduction of the labor force.[1] As a consequence, excess mortality occurs and adjusts the size of the labor force downwards, so as to make the supply of humans equal to the demand for labor. In a pure market economy, humans are commodities whose supply is adjusted to the demand, an unacceptable corollary.[2]

Beyond ethical concerns, interactions between market forces and mortality raise also serious difficulties for *measurement* purposes. In particular, the measurement of poverty, defined as human deprivation, is made difficult by the presence of mechanisms adjusting the population size downwards. As this was underlined by Sen (1998) and Kanbur and Mukherjee (2007), the excess mortality of persons living in poverty tends to make poverty measures biased downwards. The excess mortality faced by poor persons tends to make poor persons under-represented in statistical samples used for the measurement of poverty. Following Sen's emphasis on the 'missing women' problem, this measurement bias was coined the 'missing poor' problem. The 'missing poor' problem points to a kind of paradox for poverty measurement: poverty, by implying excess mortality, tends to make some poverty disappear, and, hence, tends to make poverty less visible from a statistical perspective.

The missing poor problem questions the *comparability* of standard poverty measures across time and across space. From an intertemporal perspective, apparent reductions in headcount poverty rates may be caused either by a reduction of human deprivation (which is the usual interpretation of a fall of measured poverty), or, on the contrary, by a rise of downward population adjustments through higher mortality among the poor.[3] These two explanations are obviously not the same at all, and policy evaluations based on misinterpretations of poverty measures may lead to serious policy errors.

[1] See *The Wealth of Nations*, Book I, chapter 8.

[2] This observation served as a starting point of Marx's critique of pure market economies. See Marx (1844) *The First Critique of Political Economy*, also known as the *Economic and Philosophical Manuscripts*, (part 1, chapter 2).

[3] A third possible explanation of a decline of headcount poverty rates consists of an improvement of survival conditions of the non-poor subpopulations, whereas the deprivation faced by poor persons would remain unchanged. Such a change, by increasing the proportion of non-poor persons in the population, tends to mechanically reduce the headcount poverty rate without any actual improvement in the situation of poor persons (see *infra*).

From an international perspective, observed poverty gaps across countries may be due either to real differences in the extent of human deprivation across these countries, or, alternatively, to differences in the strength of the mortality corrections reducing the size of the population in poverty. Here again, the two explanations are far from equivalent, and mixing these two may lead to mistaken international comparisons of poverty.[4]

As this appears clearly in the light of Smith's (1776) early discussion of pure market economies, the missing poor bias in poverty measures is likely to be more substantial in economies where the Welfare State is less developed. Indeed, in (quasi) pure market economies, few, if any, mechanisms can weaken the force of adjustments through mortality, and, hence, can avoid the distortion of poverty measures. This observation leads us to ask the following questions. How large is the missing poor bias in developing and least developed countries? How does the missing poor bias affect, or even pollute, the international comparison of poverty across developing or least developed countries? Which institutional factors affect the size of the missing poor bias and, in particular, does the coverage of a country's health system causally reduce it?

This paper proposes to use data on income distribution and life expectancy by wealth quintiles from 92 developing and least developed countries to quantify the missing poor bias around the world. Our focus on 92 developing and least developed countries is motivated by the reasonable assumption that it is in those countries that obstacles to mortality adjustments due to pure market forces are likely to be the weakest, and, hence, it is in those countries that comparability problems faced by standard headcount poverty rates under income-differentiated mortality are likely to be the most acute. In order to quantify the missing poor bias in each country under study, we compare the actual headcount poverty rate with the hypothetical headcount poverty rate that would prevail in the case where all citizens of the country (whether they are in poverty or not) face the survival conditions of the top wealth class.

It can be shown that the hypothetical headcount poverty rate computed while assuming that all income classes face the same survival conditions satisfies not only the property of *scale invariance* (that is, insensitivity to the size of cohorts in the country), but, also, the property of *selection invariance* (that is, insensitivity to changes in income-specific survival conditions), unlike standard headcount poverty rates (which satisfy scale invariance but not selection invariance). Moreover, the choice to take the survival conditions faced by the top income class as a benchmark is motivated

[4]This point is illustrated by Lefebvre et al. (2019) by means of data on old-age poverty (age 60 and more) in Europe. Lefebvre et al. (2019) show that, according to standard headcount poverty rates, poverty is higher among the senior in Portugal than in Estonia. However, once they control for the higher mortality among the poor in Estonia, it turns out that old-age poverty is higher in Estonia than in Portugal. Baland et al. (2025) propose a Poverty Adjusted Life Expectancy index that jointly accounts for income deprivation and mortality risk, and show that standard cross-country poverty rankings can be overturned once survival conditions are taken into account.

by the fact that this amounts to construct a thought experiment which consists of the best feasible hypothetical situation (feasible in the sense that these survival conditions can be achieved in the country under study, since these are achieved by the top income class of that country).

Anticipating our results, we show that correcting population structures for income-differentiated mortality leads to sizable revisions in both the size and the composition of the population, with direct implications for poverty measurement. Because individuals in lower income classes face higher mortality risks, they are disproportionately "missing" from observed populations, implying that standard poverty measures, that are computed on survivors, systematically understate true deprivation. Aggregated across the sample, the adjustment of headcount poverty rates across the 92 countries reveals the existence of an invisible continent of uncounted poverty comprising over 116 million additional poor persons, who would have been counted as poor provided they were not the victims of income-based selection processes, but were not counted as poor because of their premature death. This invisible continent of uncounted poverty illustrates that the selection bias due to income-differentiated mortality is not a marginal issue for the measurement of deprivation around the world. On the contrary, it raises serious concerns for the quantification of human deprivation around the world. Moreover, adjusting for this missing poor bias yields not only significant upward revisions in poverty headcounts but can also alter cross-country poverty rankings. The magnitude of these corrections is large and heterogeneous and reflects differences in mortality inequality across countries.

We then ask what accounts for this variation and find that it is to a large extent a health system phenomenon. The bias has two structural sources, a gradient channel capturing how sharply mortality rises with income, and a density channel capturing the mass of households sitting near the poverty line. We target the gradient channel by measuring health system quality by the Universal Health Coverage (UHC) service coverage index. In addition, we instrument it with the malaria ecology index of Kiszewski et al. (2004) which is a predetermined feature of the disease environment that shaped the historical development of health systems. The results show that a ten point gain in coverage lowers the missing poor bias by about one percentage point. Coverage also significantly flattens the income-mortality gradient itself, which confirms that the effect operates through the gradient rather than through the shape of the income distribution. Poverty is therefore most understated precisely in the countries whose health systems are least able to prevent the deaths that cause the understatement.

In sum, this paper shows that, although the existence of downward adjustments of the size of the population due to poverty is well-known since Smith (1776) and Malthus (1798), it is still the

case, in the 21st century, that standard headcount poverty measures are biased downward because of these population adjustment mechanisms. These mechanisms act as selection devices making the deprived populations under-represented in statistics used for the measurement of poverty. Moreover, the fact that the size of the missing poor bias varies strongly across countries implies that the comparability of standard headcount poverty measures can be questioned. Comparing measures of poverty in economies where the strength of population adjustments are highly unequal can lead to misleading interpretations, and to erroneous policy assessments. Finally, this paper shows that the strength of those population adjustments is not arbitrary. It is governed in large part by the coverage of the health system, so that the countries whose poverty is most understated are also those least equipped to prevent the premature deaths that cause the understatement.

This paper is related to several branches of the literature. First of all, it is related to the large literature dedicated to the empirical study of the mortality/income and the mortality/wealth relationships, such as, among others, Pamuk (1985, 1988), Duleep (1986), Deaton and Paxson (1998),Backlund et al. (1999), Deaton (2003), Jusot (2004), Bossuyt et al. (2004), Van Oyen et al. (2005), Snyder and Evans (2006), Duggan et al. (2008), Cristia (2009), Salm (2011), Belloni et al. (2013), Kalwij et al. (2013), Chetty et al. (2016) and Milligan and Schirle (2021). We complement that literature by estimating life expectancy statistics by income class for 92 developing and least developed countries, and by exploring the implications of these relationships for poverty measurement around the world. Second, this paper is also strongly linked to the increasingly large literature dedicated to the missing poor bias in poverty measurement, such as Sen (1998), Kanbur and Mukherjee (2007), Lefebvre et al. (2013, 2018, 2019); Lefèbvre et al. (2019); Lefebvre et al. (2023, 2024). Whereas these previous studies of the missing poor problem focused on Europe (Lefebvre et al., 2018, 2019; Lefèbvre et al., 2019; Lefebvre et al., 2023) or on the U.S. (Lefebvre et al., 2024), our contribution to this literature lies in our emphasis on the quantification of the missing poor bias in least developed countries across the five continents. The present paper is also related to other works examining the issue of poverty measurement under unequal longevity, such as Baland et al. (2021) and Baland et al. (2025). Note that these papers consider a two-dimensional approach to poverty, where each person dying before a threshold age is counted as poor (independently from the income-mortality relationship). The present paper differs from these studies, by remaining in the usual one-dimensional poverty assessment, but examines how standard one-dimensional poverty headcount measures are polluted by income-differentiated mortality. Our approach is thus clearly complementary to the one of Baland et al. (2021), Decerf et al (2021) and Baland et al. (2025).

This paper is organized as follows. Section 2 provides some theoretical background on the mea-

surement of poverty when the strength of mortality varies depending on the extent of material deprivation. Section 3 presents the data for the 92 least developed and developing countries under study, as well as the methods used for the estimation of income distributions and of life expectancies by income across countries. Section 4 quantifies the missing poor bias across the 92 countries, and derives the implications of these results for the comparison of poverty around the developing world. Section 5 examines the structural drivers of cross-country variation in the bias, focusing on the causal effect of health system quality on the income-mortality gradient and providing IV estimates using malaria ecology as an instrument for UHC coverage. Conclusions are left to Section 6.

2 Theoretical background

Basic framework Let us consider an economy where a constant cohort of size $N_0 > 0$ is born at any period.[5] The maximal duration of life is equal to $\ell > 1$. Denoting the number of individuals of age $i \in \{0, ..., \ell - 1\}$ by N_i, the total population size is:

$$N = \sum_{i=0}^{\ell-1} N_i \tag{1}$$

In that economy, there exist $n > 1$ income classes, which are indexed in an increasing order, from 1 to n:

$$y^1 < ... < y^z < ... < y^n \tag{2}$$

Throughout this paper, we denote by y^z the absolute poverty line. For the sake of simplicity, we take this poverty line as given and fixed once and for all.

Let us denote by N_i^k the number of persons of age i who belong to the income class k. Given that $N_i = \sum_{k=1}^{n} N_i^k$, the total number of persons is:

$$N = \sum_{i=0}^{\ell-1} \sum_{k=1}^{n} N_i^k \tag{3}$$

The headcount poverty rate (HC) for the entire population is equal to:

$$HC = \frac{\sum_{i=0}^{\ell-1} \sum_{k=1}^{z} N_i^k}{\sum_{i=0}^{\ell-1} \sum_{k=1}^{n} N_i^k} \tag{4}$$

[5] This assumption is equivalent to assuming that fertility is constant over time and equal to its replacement level.

The headcount poverty rate HC is not invariant to the survival conditions that are at work in the economy. Indeed, survival conditions determine the proportions of individuals that survive from one age to the next age, and, hence, determine the sizes of the different age groups N_i. But this is not the only influence of survival conditions on HC: survival conditions determine also, within each age group N_i, the sizes of the different income classes N_i^k. Harsher living conditions for the poor tend to imply harsher survival conditions for them, and, hence, lower proportions of survivors among the poor at later ages of life.

Effects of mortality on the headcount poverty rate In order to decompose the various effects of mortality on the measurement of poverty, let us assume that, in each new cohort, there is a fraction ϕ^k of individuals in income class k:

$$N_0 = \sum_{k=1}^{n} N_0^k = \sum_{k=1}^{n} \phi^k N_0 \tag{5}$$

where $\sum_{k=1}^{n} \phi^k = 1$.

Let us denote by s_i^k the (unconditional) probability of survival to age i for a person in income class k:

$$s_i^k = \prod_{j=0}^{i-1} (1 - d_j^k)$$

where d_j^k is the probability of death for a person of age j belonging to income class k. As usual we assume $s_0^k = 1$.

Throughout this paper, we will assume, for the sake of simplicity, that income mobility across the ages of life is negligible. This assumption will allow us to focus on the 'pure' effect of income-specific survival conditions on the measurement of poverty, without taking into account interferences from the income mobility process.[6]

Under a negligible income mobility, the size of each income class k at a given age i depends only on the size of the same income class k at age $i-1$ and on the income-specific mortality rate d_{i-1}^k. Hence, we obtain that the number of individuals of age i who belong to income class k can be

[6] Assuming no income mobility is an obvious simplification. This assumption is made in order to look at the pure effect of income-specific survival conditions on the sizes of the different income classes. Once mobility is introduced, the size of all income classes depends on the survival conditions of all income classes, which makes the analysis of selection effects more complex (see Lefebvre et al 2019). Beyond the issue of simplicity, this assumption is also driven by the lack of data on mobility in the 98 least developed countries studied in the paper (see *infra*).

rewritten as:

$$\begin{aligned} N_i^k &= (1-d_{i-1}^k)N_{i-1}^k \\ &= (1-d_{i-1}^k)(1-d_{i-2}^k)N_{i-2}^k \\ &= ... \\ &= s_i^k N_0^k = s_i^k \phi^k N_0 \end{aligned} \tag{6}$$

Substituting for that expression in HC, we obtain:

$$HC = \frac{\sum_{i=0}^{\ell-1}\sum_{k=1}^{z} s_i^k \phi^k N_0}{\sum_{i=0}^{\ell-1}\sum_{k=1}^{n} s_i^k \phi^k N_0} \tag{7}$$

The simplicity of that expression is obtained thanks to the assumption of negligible income mobility. That assumption allows us to capture the 'pure' effect of income-specific survival conditions on the size of each income class across the ages of life. Without that assumption, survival conditions of all n income classes would affect the size of each of the n income classes at all ages, while being weighted by the income mobility probabilities (see Lefebvre et al 2019). We will discuss later on how our results would be affected if mobility were introduced (see *infra*).

The life expectancy at birth for individuals born in income class k is:[7]

$$L_0^k = \sum_{i=0}^{\ell-1} s_i^k \tag{8}$$

Hence, HC can, after some manipulations, be rewritten as:

$$HC = \frac{\sum_{k=1}^{z} \left(\phi^k N_0\right)\left(\sum_{i=0}^{\ell-1} s_i^k\right)}{\sum_{k=1}^{n} \left(\phi^k N_0\right)\left(\sum_{i=0}^{\ell-1} s_i^k\right)} = \frac{\sum_{k=1}^{z} \phi^k N_0 L_0^k}{\sum_{k=1}^{n} \phi^k N_0 L_0^k} \tag{9}$$

This formula makes appear that the total size of each income class k (including all ages of life) depends on the initial size of that income class in the newborn cohort $\phi^k N_0$, and on the income-specific survival conditions summarized by the income-specific life expectancy L_0^k.

Given that the constant size of new cohorts N_0 appears at the numerator and at the denominator

[7] That formula assumes implicitly that a person dying during a year dies at the beginning of that year.

of HC, it is possible to simplify that expression as follows:

$$HC = \frac{\sum_{j=1}^{z} L_0^j \phi^j}{\sum_{i=1}^{n} L_0^i \phi^i} \tag{10}$$

The headcount poverty rate is thus invariant to the size of (constant) cohort size. We have $\frac{\partial HC}{\partial N_0} = 0$. This property, which can be coined *scale invariance*, is an attractive feature of HC: this guarantees that the comparison of poverty measures across time periods or across countries is not affected by the absolute sizes of the populations under comparison.

The above rewriting exercise makes also appear that the standard headcount poverty rate depends on income-specific life expectancies. Indeed, it is only in the special case where all income classes face the same survival conditions, that is, when:

$$L_0^i = L_0 \quad \forall i = 1, ..., z, ..., n$$

that the headcount poverty rate can be simplified to:

$$HC = \sum_{i=1}^{z} \phi^i \tag{11}$$

which captures the real prevalence of the poverty phenomenon, all size effects and survival effects being neutralized. The right-hand-side of that expression can be regarded as the 'basic' or 'fundamental' poverty.

In all the other cases, where survival conditions vary across income classes, the headcount poverty rate does depend on the extent to which survival conditions differ based on the material living conditions.

In general, survival conditions tend to deteriorate with the extent of material deprivation, so that:

$$L_0^1 < ... < L_0^z < ... < L_0^n \tag{12}$$

As a consequence of income-differentiated mortality, the numerator of HC, which depends on life expectancies for individuals living below the poverty line, tends to be reduced relatively to the denominator of HC, which depends on all life expectancies (which are, on average, higher than life expectancies below the poverty line). This implies that poor persons tend to be under-represented

in standard HC poverty measures. This phenomenon is the *missing poor bias*.

Quite paradoxically, a worsening of the survival conditions faced by the poor tends to reduce - rather than increase - the HC ratio. Indeed, we have:

$$\left.\frac{\partial HC}{\partial L_0^k}\right|_{k<z} = \frac{\phi^k \left(\sum_{i=1}^{n} L_0^i \phi^i\right) - \left(\sum_{j=1}^{z} L_0^j \phi^j\right) \phi^k}{\left[\sum_{i=1}^{n} L_0^i \phi^i\right]^2} = \phi^k \frac{\left(\sum_{i=z+1}^{n} L_0^i \phi^i\right)}{\left[\sum_{i=1}^{n} L_0^i \phi^i\right]^2} > 0 \tag{13}$$

This feature is not an attractive characteristic of HC as a measure of poverty. Clearly, we would like the poverty measure to satisfy some form of *invariance to survival conditions* or *selection invariance* (similar, in spirit, to scale invariance), that is: $\frac{\partial HC}{\partial L_0^k} = 0$. Indeed, such an invariance to survival conditions would prevent the unattractive implication that measured poverty declines when the survival conditions faced by the poor deteriorate (see Lefebvre et al 2013).

It should be stressed here that, if we were allowing for non-negligible income mobility, the result $\left.\frac{\partial HC}{\partial L_0^k}\right|_{k<z} > 0$ would not necessarily prevail. A first difficulty would be that one could no longer look at the effect of life expectancy L_0^k on the headcount poverty rate, since all survival probabilities (from all income classes) would jointly determine the size of each income class. It would then be necessary to look at the sign of $\left.\frac{\partial HC}{\partial s_i^k}\right|_{k<z}$ instead of $\left.\frac{\partial HC}{\partial L_0^k}\right|_{k<z}$ (because income-specific life expectancies would disappear from the formulas, and be replaced by sums of products of survival conditions of different income classes). Moreover, looking at the effect of a single survival probability s_i^k on HC would yield ambiguous results, since the survival conditions of each income class would then affect the size of each income class through the income mobility process (see Lefebvre et al 2019). However, provided income mobility remains small enough (i.e., a large probability mass on the diagonal of the income mobility matrix), the survival conditions specific to an income class would still be decisive in the size of that income class across the ages of life, other influences being secondary. Our result is thus qualitatively robust as long as income mobility is only a secondary force.

Another unattractive feature of HC related to the existence of income-specific survival conditions is that HC decreases following a gain in life expectancy only enjoyed by a non-poor segment of the population, whereas the deprivation of the poor segment of the population is left unchanged. Indeed, we have also:

$$\left.\frac{\partial HC}{\partial L_0^k}\right|_{k\geq z} = \frac{-\left[\sum_{j=1}^{z} L_0^j \phi^j\right] \phi^k}{\left[\sum_{i=1}^{n} L_0^i \phi^i\right]^2} < 0 \tag{14}$$

Thus any improvement in the survival conditions faced by non-poor persons contributes, *ceteris paribus*, to reduce the standard headcount poverty rate, despite the fact that there has been no improvement in the living conditions faced by deprived persons.

Selection invariance, that is, invariance of the poverty measure to a change in a group-specific survival conditions L_0^k, is an appealing property for a measure of poverty, since this property immunizes the measure of poverty to apparent reductions in measured poverty that would be due either to a worsening of the survival conditions faced by the poor, or to an improvement of the survival conditions faced by the non-poor. Note that it is only in the special case of no differences in survival conditions across all income classes (that is, when $L_0^i = L_0^j \; \forall i \neq j$) that HC would satisfy selection invariance. But that special case is a non-generic case. Hence, it is necessary to adjust HC in order to make it satisfy selection invariance in all cases.

Correcting the headcount poverty rate In order to make the poverty measure invariant to survival conditions, a simple approach consists of modifying HC as follows. One can, as suggested by Lefebvre et al (2013), compute the hypothetical headcount poverty rate HC^C that would prevail if all income classes were facing the *same* survival conditions.

The adjusted headcount poverty rate, denoted by HC^C, is:

$$HC^C = \frac{\sum_{k=1}^{z} L_0^R \phi^k N_0}{\sum_{k=1}^{n} L_0^R \phi^k N_0} \tag{15}$$

where L_0^R denotes a life expectancy of reference, supposed to apply to all income classes.

Regarding the selection of the reference survival conditions, a natural candidate consists of the survival conditions faced by the top income class, that is, L_0^n. The underlying intuition supporting the selection of L_0^n as a benchmark goes as follows. Using the survival conditions of the top income class as a reference leads us to an experiment of thought that consists of considering a hypothetical world where all individuals could enjoy the same survival conditions as the ones enjoyed by the richest individuals. Note that this is, in some sense, the best feasible world (because the survival conditions of the richest are feasible).

It should be stressed, however, that alternative reference survival conditions could be used as a reference. But in any case, whether the level of the reference life expectancy L_0^R is, the adjusted headcount poverty rate HC^C exhibits some attractive properties. First, HC^C satisfies, like HC, scale invariance, because HC^C is, like HC, a ratio that does not depend on the total size of cohorts at birth N_0. Hence we have: $\frac{\partial HC^C}{\partial N_0} = 0$, like in the case of the standard headcount ratio HC.

Moreover, HC^C satisfies also selection invariance, since we have: $\frac{\partial HC^C}{\partial L_0^R} = 0$. To see this, note that, given that L_0^R weights all terms both at the numerator and at the denominator of HC^C, the factor L_0^R can be simplified from the formula of HC^C, which becomes:

$$HC^C = \sum_{k=1}^{z} \phi^k \tag{16}$$

As such, the corrected headcount ratio HC^C captures what we called above the 'basic' or 'fundamental' deprivation of the population, abstracting from all noise induced by size effects and selection effects. The corrected ratio HC^C is not only invariant to the scale of the population - like HC -, but, also, to the survival processes at work, unlike HC. Indeed, we have:

$$\frac{\partial HC^C}{\partial L_0^k} = 0 \ \forall k \tag{17}$$

The equality $\frac{\partial HC^C}{\partial L_0^k} = 0$ implies that HC^C satisfies selection invariance. Unlike HC, the adjusted measure HC^C does not go down when the survival conditions of the poor worsens. Neither does HC^C go down when the survival conditions of the non-poor improve. HC^C is thus not vulnerable to income-based selection biases, unlike HC.

These two invariance properties - scale invariance and selection invariance - make HC^C an attractive measure for poverty. Moreover, comparing the levels of HC^C with the one of the standard headcount poverty rate HC (which violates, in non-generic cases, selection invariance) gives an idea of the extent of the missing poor bias, that is, the downward bias in measured poverty that is due to income-based selection. The remainder of this paper is dedicated to that task.

3 Data and method

In order to compute the missing poor bias we need for each country, a granular income distribution and life expectancy estimates by income. Neither is directly observed for our sample of countries. So we construct both from grouped data using standard parametric methods and then combine them to produce the survival-adjusted poverty counts described in Section 2. The procedure follows three steps, each described in a subsection below: (i) fitting a continuous income distribution to decile means; (ii) estimating a socioeconomic mortality gradient from quintile life expectancy data; and (iii) reweighting income classes by their counterfactual population shares under equal survival conditions. Figure A.1 in Appendix A.2 summarises the pipeline schematically.[8]

[8] All country-level inputs are reported in Appendix A.1.

We draw on three main sources. Income distribution data come from the World Bank's Poverty and Inequality Platform (Bank, 2024) and the UNU-WIDER World Income Inequality Database (UNU-WIDER, 2025). For each country we use the most recent available data, which reports mean income by decile. Life expectancy by wealth quintile is estimated from data obtained through the United Nations Inter-agency Group for Child Mortality Estimation (UN IGME). It covers 96 countries with five quintile-level observations each (see below). Population data are from the World Development Indicators.

Our working sample consists of 92 developing and least-developed countries for which all three data elements are available and the estimated wealth-mortality gradient is positive; that is the richest quintile has strictly higher life expectancy than the poorest.[9] The sample spans all World Bank regions and covers a population of approximately 4.5 billion.

3.1 Step 1: Reconstructing the income distribution

Parametric approach. We fit a lognormal distribution to the ten observed decile means for each country. The lognormal is the standard workhorse for income distribution estimation from grouped data. It captures the positive skewness and heavy right tail characteristic of most income distributions and admits closed-form expressions for within-decile means, which facilitates estimation (Kleiber and Kotz, 2003; Kakwani and Podder, 1973).[10]

Let individual income Y follow $\ln Y = \mu + \sigma Z$, $Z \sim \mathcal{N}(0,1)$, with parameters $(\mu, \sigma) \in \mathbb{R} \times \mathbb{R}_{++}$. Under this assumption, the model-implied mean income within decile d is:

$$\mathbb{E}[Y \mid p_{d-1} < F(Y) \leq p_d] = \exp\!\big(\mu + \tfrac{1}{2}\sigma^2\big)\, \frac{\Phi(z_d - \sigma) - \Phi(z_{d-1} - \sigma)}{p_d - p_{d-1}}, \tag{18}$$

where $p_d = d/10$, $z_d = \Phi^{-1}(p_d)$, and $\Phi(\cdot)$ is the standard normal CDF. This yields ten moment conditions linking (μ, σ) to the observed decile means $\bar{y}_d$. We estimate the parameters by nonlinear least squares:

$$(\hat{\mu}, \hat{\sigma}) = \arg\min_{\mu,\, \sigma > 0} \sum_{d=1}^{10} \big[\bar{y}_d - \mathbb{E}[Y \mid p_{d-1} < F(Y) \leq p_d;\, \mu, \sigma]\big]^2. \tag{19}$$

[9] We exclude four countries (Albania, Equatorial Guinea, and Serbia) where the estimated gradient is negative. Negative gradients likely reflect measurement error in the quintile life expectancy data, arising from small cell sizes in the underlying health surveys or from the use of wealth rather than income as the stratifying variable in settings where the two measures are weakly correlated.

[10] More flexible alternatives, such as the generalised beta of the second kind (GB2), Pareto–lognormal mixtures, and generalised Pareto curves, may fit the upper tail more precisely (McDonald, 1984; Hajargasht and Griffiths, 2013; Blanchet et al., 2022). We have assessed the sensitivity of our results to these alternatives and although the final numbers are obviously not exactly the same, it does not affect the global sense of our analysis in this paper.

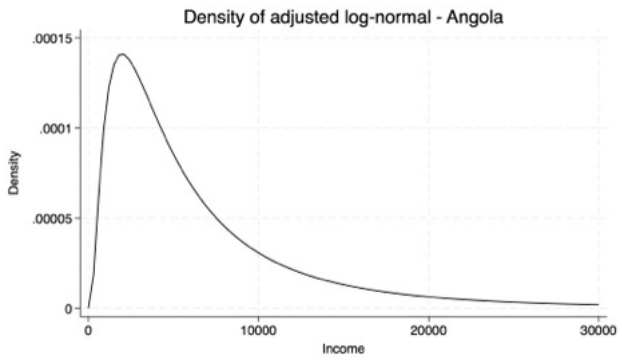
The system is overidentified since we have two parameters and ten moments, so the estimator recovers the best-fitting lognormal in a least-squares sense rather than interpolating all decile means exactly. The degree of overidentification provides a natural goodness-of-fit diagnostic (Shorrocks and Wan, 2008; Hajargasht et al., 2012).

Discretisation. The fitted distribution is evaluated on a grid of 100 equally spaced income classes, yielding population shares and midpoint income values for each class. These 100 classes are the unit of analysis for all subsequent steps. The population reconstruction is accurate and when we compare the implied total population to census figures, the gap is below 2% for the vast majority of countries (see Appendix A.1).

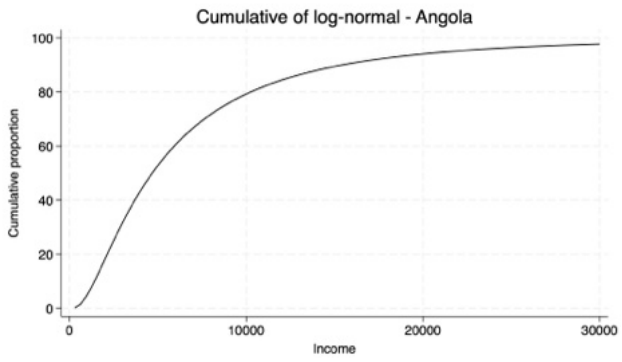
Illustration. Figure 1 illustrates the procedure for Angola. The fitted lognormal density and CDF are shown in panels (a) and (b); panel (c) presents the resulting frequency distribution across the 100 income classes. Angola's income distribution is strongly right-skewed, with the modal income class well below the mean, a pattern representative of the Sub-Saharan African countries in our sample.

Figure 1: Income distribution reconstruction - Angola

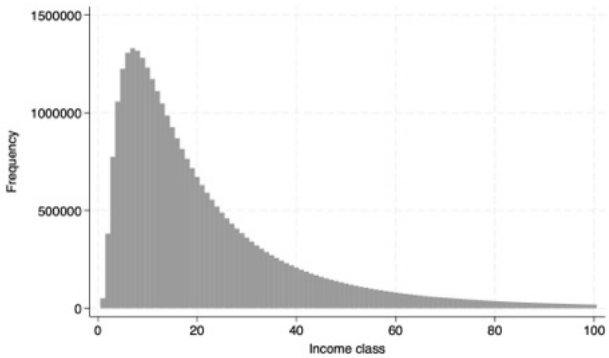
(a) Density



(b) CDF



(c) Frequency (100 classes)



Notes: Lognormal parameters estimated by nonlinear least squares on ten decile means (PIP/WIID). Income expressed in 2017 PPP USD. See Appendix A.3 for all countries.

3.2 Step 2: Estimating life expectancy by income class

Data constraints and the role of wealth quintiles. The ideal input for our exercise would be life expectancy disaggregated directly by income group. Such data do not exist for most countries in our sample. Household surveys in low- and middle-income countries do not systematically record income alongside mortality outcomes. The closest available proxy is life expectancy by wealth quintile. Wealth quintiles are routinely constructed in Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) from household asset indices, and the United Nations Inter-agency Group for Child Mortality Estimation (UN IGME) has assembled a dataset of under-5 mortality rates (U5MR) disaggregated along this dimension for a large number of countries[11]. We rely on this dataset as our socioeconomic mortality gradient, justified by a substantial empirical literature documenting that income rank and wealth rank are strongly correlated and generate similar gradients with respect to health and mortality outcomes Pamuk (1985); Killewald et al. (2017); Stelzer (2023); Smith (1999).

Life expectancy by wealth quintile. Because vital registration is incomplete in most countries in our sample, age-specific mortality rates by wealth quintile cannot be directly observed. We therefore convert each quintile-specific U5MR into a life expectancy at birth using the UN extended Coale-Demeny West model life tables, which map a single child-mortality indicator to a complete age profile of mortality.[12] The tables are linearly interpolated to one decimal point of life expectancy, and for each country-quintile cell we select the level whose U5MR most closely matches the observed value. This is done using the same Coale-Demeny family as UN IGME to ensure internal consistency. We then obtain L_q for each wealth quintile $q \in \{1, \ldots, 5\}$

From wealth quintiles to a continuous income gradient. Thus life expectancy data are available by wealth quintile, not by income class. We bridge this gap in two stages. First, we estimate a linear socioeconomic gradient of life expectancy on wealth rank. Second, we use this gradient to impute life expectancy for each of the 100 income classes, assuming that income rank and wealth rank are comparable proxies for socioeconomic position; an assumption supported by a substantial empirical literature documenting strong income-wealth correlations across a range of country

[11] The wealth index used in these surveys is a composite measure of household living standards based on asset ownership, housing materials, and access to water and sanitation; all households are ranked on a continuous scale and split into five quintiles.

[12] The wealth index ranks all surveyed households on a continuous scale of living standards — based on asset ownership, housing materials, and access to water and sanitation — and groups them into five quintiles. DHS and MICS use identical methodology for this index.

contexts.[13]

Gradient estimation. For each country, we assign each wealth quintile $q \in \{1, \ldots, 5\}$ a relative socioeconomic rank equal to its population midpoint: $M_q = 10 + 20(q-1)$, so $M_1 = 10\%$, $M_2 = 30\%$, $\ldots$, $M_5 = 90\%$. We then estimate the weighted OLS regression:

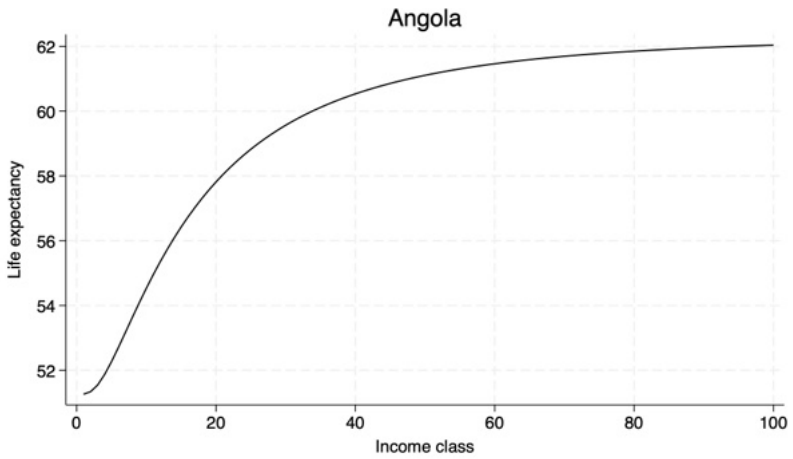
$$L_q = \alpha + \beta\, M_q + \varepsilon_q, \tag{20}$$

where L_q denotes life expectancy at birth for quintile q. The regression is weighted by each quintile's population share (0.20 throughout). The slope $\hat{\beta}$ measures the increase in life expectancy associated with a one-percentile-point rise in socioeconomic rank; extrapolated over the full 0–100 range, it captures the life-expectancy gap between the bottom and the top of the wealth distribution. This strategy follows the approach of Lefebvre et al. (2019) and is consistent with epidemiological studies modelling mortality gradients by socioeconomic rank (Pamuk, 1985, 1988). Country-specific gradient estimates are reported in Appendix A.4.

Imputation and illustration. Each of the 100 income classes is assigned the percentile rank corresponding to its midpoint, and predicted life expectancy $\hat{L}_k$ is obtained by evaluating equation (20) at that rank. Figure 2 shows the resulting profile for Angola. Life expectancy rises from approximately 52 years in the lowest income class to 62 years at the top, a 10-year gradient that is broadly representative of the Sub-Saharan African countries in our sample. The full set of country profiles is presented in Appendix A.5.

[13] Multi-year income and net wealth are positively correlated with coefficients around 0.6 in U.S. microdata (Kilewald et al., 2017). Cross-country analyses confirm this pattern in euro-area surveys (Stelzer, 2023) and both measures exhibit similar gradients with respect to health and mortality (Pamuk, 1985; Smith, 1999; Mackenbach et al., 2005; Zaninotto et al., 2018). Intergenerational transmission of housing wealth further tightens the long-run link between the two (Daysal et al., 2022).

Figure 2: Life expectancy by income class — Angola

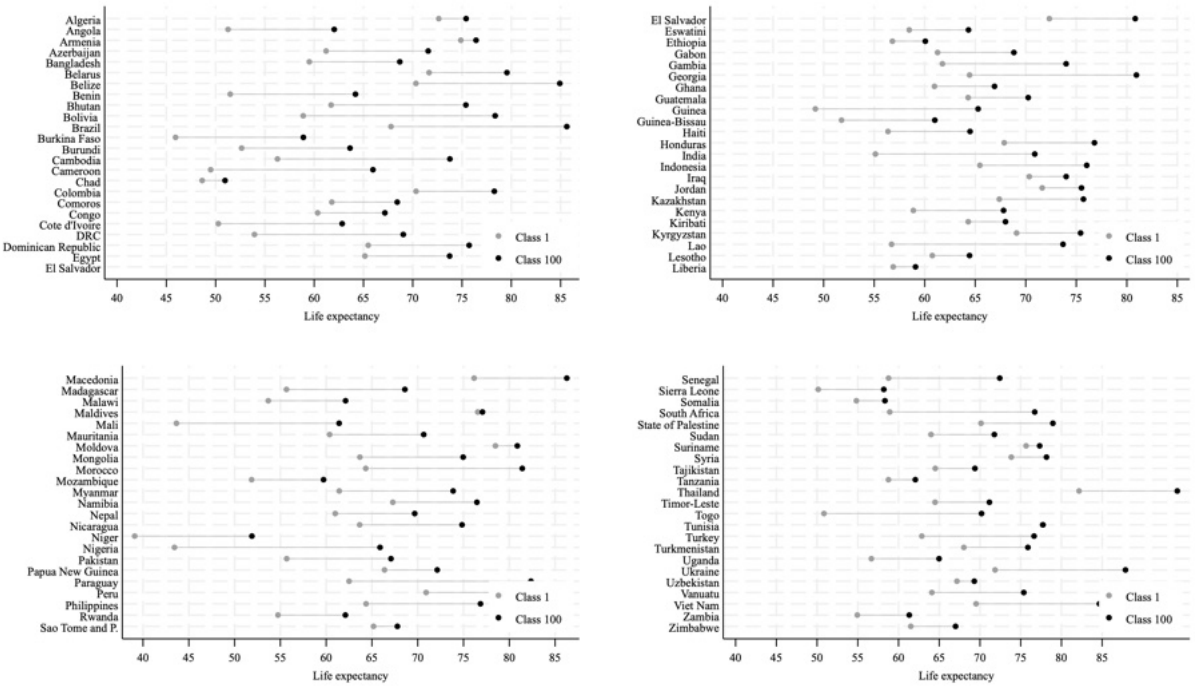


Notes: Predicted life expectancy from the weighted OLS gradient estimated on five wealth quintile observations. Horizontal axis: income class rank (1 = poorest, 100 = richest).

3.3 Step 3: Reweighting and the adjustment factor

The life-expectancy gap as a sufficient statistic. Figure 3 reports, for each country in our sample, the difference in predicted life expectancy between the poorest and the richest income class, $\hat{L}_{100} - \hat{L}_1$. This gap summarises the socioeconomic mortality gradient and provides an intuitive measure of within-country longevity inequality. The longer the horizontal bar, the larger the survival disadvantage of the poor. The dispersion across countries is striking and goes from near-zero gaps in some Central Asian economies to differentials approaching 20 years in parts of Sub-Saharan Africa and Latin America. Crucially, this gap is not merely descriptive. From equation (10), the standard headcount poverty rate weights each income class by its life expectancy, so a larger gap implies a larger downward bias in measured poverty. Figure 3 therefore serves as a sufficient statistic for the direction and approximate magnitude of the selection bias we seek to correct.

Figure 3: Life-expectancy gap between poorest and richest income class, by country



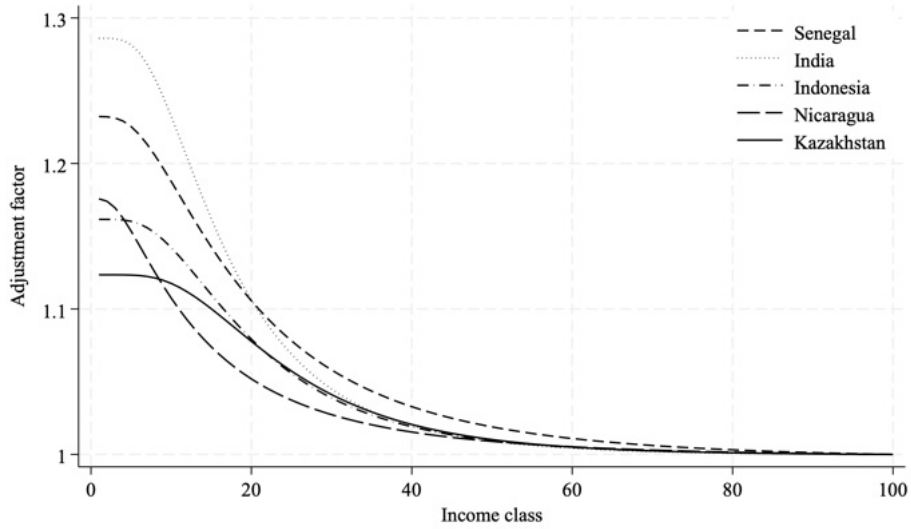
Notes: Each horizontal segment spans the predicted life expectancy of income class 1 (left endpoint) to income class 100 (right endpoint), derived from the weighted OLS gradient in equation (20). Countries are sorted by gap size. See Appendix A.4 for numerical values.

Adjustment factors. We translate the life-expectancy profile into a population reweighting by defining, for each income class k, the adjustment factor:

$$A_k = \frac{\hat{L}_{100}}{\hat{L}_k}. \tag{21}$$

A_k measures the proportional increase in the size of income class k that would result from equalising survival conditions to those of the top class. Multiplying the observed population count of class k by A_k yields the counterfactual population under equal longevity. By construction $A_{100} = 1$ and $A_k > 1$ for all $k < 100$, with the correction largest at the bottom of the distribution where the life-expectancy gap is widest. Figure 4 illustrates this reweighting schedule for five representative countries. Steeper mortality gradients (as in Senegal and India) translate into more convex adjustment profiles, while flat gradients (as in Kazakhstan) generate near-uniform adjustments close to one.

Figure 4: Adjustment factor by income class — selected countries



Notes: $A_k = \hat{L}_{100}/\hat{L}_k$ for each income class k. Countries selected to illustrate the range of gradient steepness in the sample. Full country-level adjustment factors are reported in Appendix A.1.

The adjustment factors do not alter the income shares at birth; they neutralise only differential survival. The resulting correction therefore isolates a pure selection effect: how much the lower tail of the income distribution is mechanically compressed by premature mortality among the poor. The survival-adjusted population counts serve as the direct input to the corrected headcount poverty rate HC^C defined in equation (16).

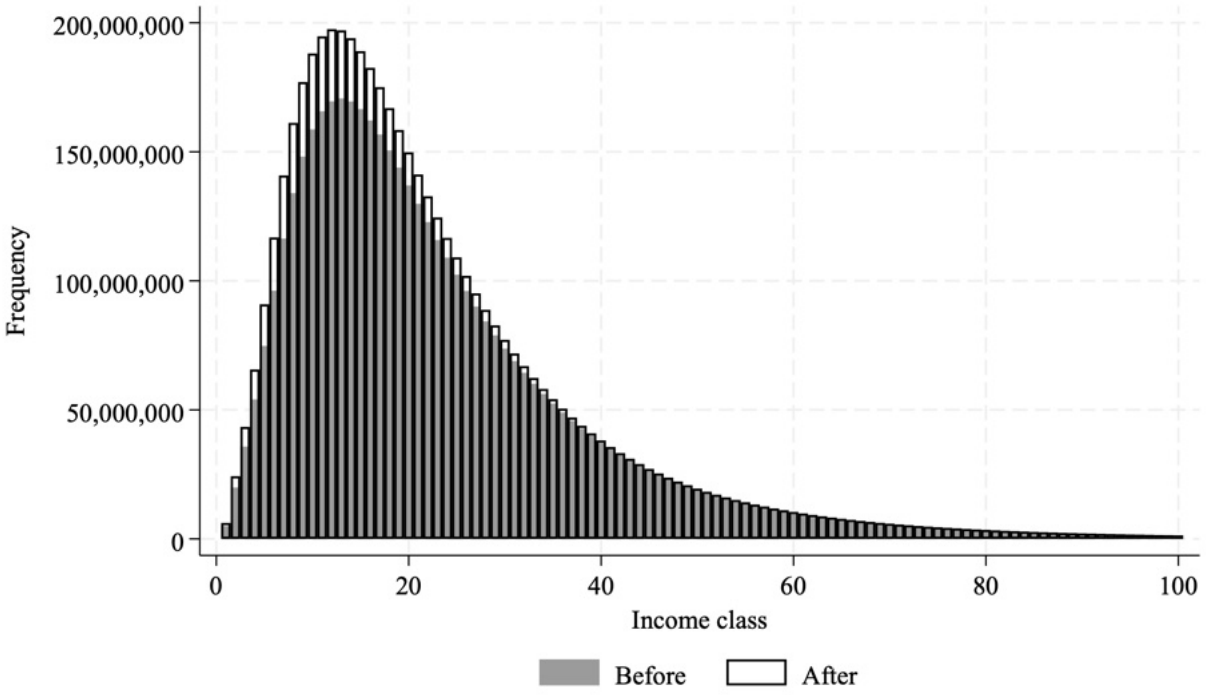
4 The missing poor bias

We now quantify the magnitude of the selection bias induced by income-differentiated mortality. Using the adjustment factors derived in the previous section, we construct, for each country, a counterfactual income distribution in which all income classes face the life expectancy of the top income group. This exercise isolates a pure mortality-selection effect by holding constant the income distribution at birth and modifying only survival probabilities across income classes. The difference between the observed and counterfactual corrected poverty rates therefore measures the extent to which standard headcount poverty mechanically understates deprivation due to premature mortality among the poor.

Reshaping the population distribution. Figure 5 superimposes the income frequency distribution before and after the mortality correction, pooling all countries in the sample. The comparison illustrates in a striking way the key mechanism at work. The correction adds population mass almost exclusively in the lower income classes, while leaving the upper part of the distribution virtually un-

changed. This asymmetry directly reflects the logic of the adjustment factor $A_k = \hat{L}_{100}/\hat{L}_k$. Since life expectancy differences between income classes are largest at the bottom of the distribution, the correction is most powerful there. The peak of the distribution shifts upward after correction, revealing that the observed distribution is not merely a scaled-down version of the counterfactual one, but a structurally compressed version of it. In other words, standard poverty measurement does not simply undercount the poor uniformly; it systematically underweights the poorest classes relative to the wealthier ones. As a result, standard population counts understate the size of disadvantaged groups and therefore is likely to mechanically reduce measured poverty.

Figure 5: Income distribution (frequency) in the sample of countries before and after the addition of missing persons



Population adjustments by region and country. Table 1 presents, for each World Bank sub-region and for the total sample, the population before and after correction and the resulting poverty headcounts. Three features of the table deserve attention. First, the population adjustment is substantial and pervasive. Across the full sample, the correction adds approximately 476 million individuals (a 10.5 percent increase) and raises the aggregate poverty rate from 20.5 to 21.4 percent, corresponding to roughly 116.6 million additional poor persons. Second, the adjustment is highly heterogeneous across regions. South Asia exhibits the largest relative population adjustment (12.4 percent), followed by Sub-Saharan Africa (11.2 percent) and Latin America and the Caribbean (10.2 percent). Yet Sub-Saharan Africa accounts for by far the largest absolute increase in measured

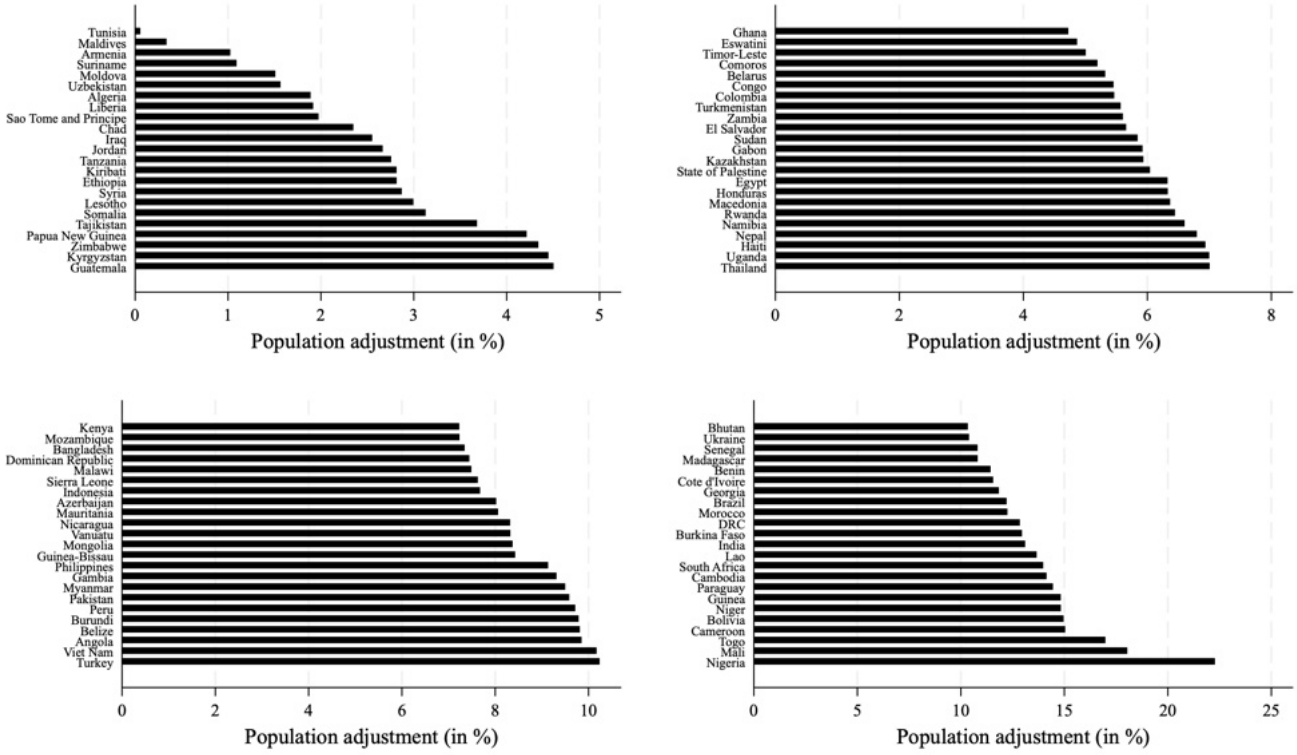
poverty, with over 86 million additional poor persons, driven by the combination of a steep mortality gradient and a very high baseline poverty rate. South Asia, despite its larger relative population adjustment, contributes 16 million additional poor, reflecting its much lower baseline poverty rate at the \$3/day threshold. Third, the Middle East and North Africa region displays the smallest relative adjustment (7.2 percent), followed closely by Europe and Central Asia (7.5 percent), consistent with more developed health systems and compressed mortality gradients in those regions.

Table 1: Population and poverty changes

	Population						
	Before	After	Correction		HC	HC^C	$HC^C - HC$
			(N)	(%)	(%)	(%)	(N)
East Asia & Pacific	650,097,339	705,684,861	55,587,522	8.6	13.7	14.4	4,737,720
Europe & Central Asia	233,586,789	251,164,394	17,577,605	7.5	3.9	4.0	275,456
Latin America & Caribbean	370,060,749	407,716,572	37,655,823	10.2	6.3	6.7	1,932,061
Middle East & North Africa (+ Afgh. & Pak.	500,516,617	536,517,153	36,000,536	7.2	4.3	4.6	7,487,447
South Asia	1,629,939,901	1,831,856,638	201,916,737	12.4	2.1	2.3	15,876,223
Sub-Saharan Africa	1,137,368,744	1,264,568,957	127,200,213	11.2	38.4	40.1	86,250,225
Total	4,521,570,139	4,997,508,575	475,938,436	10.5	20.5	21.4	116,559,132

Figure 6 disaggregates these adjustments at the country level, ranking countries from the smallest to the largest population adjustment as a share of initial population. The country-level heterogeneity is striking. At one extreme, countries such as Tunisia, Maldives and Armenia show adjustments of less than 1 percent, reflecting shallow mortality gradients and relatively compressed longevity inequality. At the other extreme, Nigeria, Cameroon and Mali exceed 20 percent, implying that more than one in five individuals is effectively missing from the observed population due to premature mortality among the poor. The adjustment exceeds 10 percent in a substantial number of countries, predominantly in Sub-Saharan Africa. This dispersion reflects the combined influence of the steepness of the mortality gradient and the size of the poor population: a steep gradient concentrated at the bottom of the income distribution generates a large upward reweighting of poor classes, amplifying the aggregate population adjustment.

Figure 6: Population adjustment in %

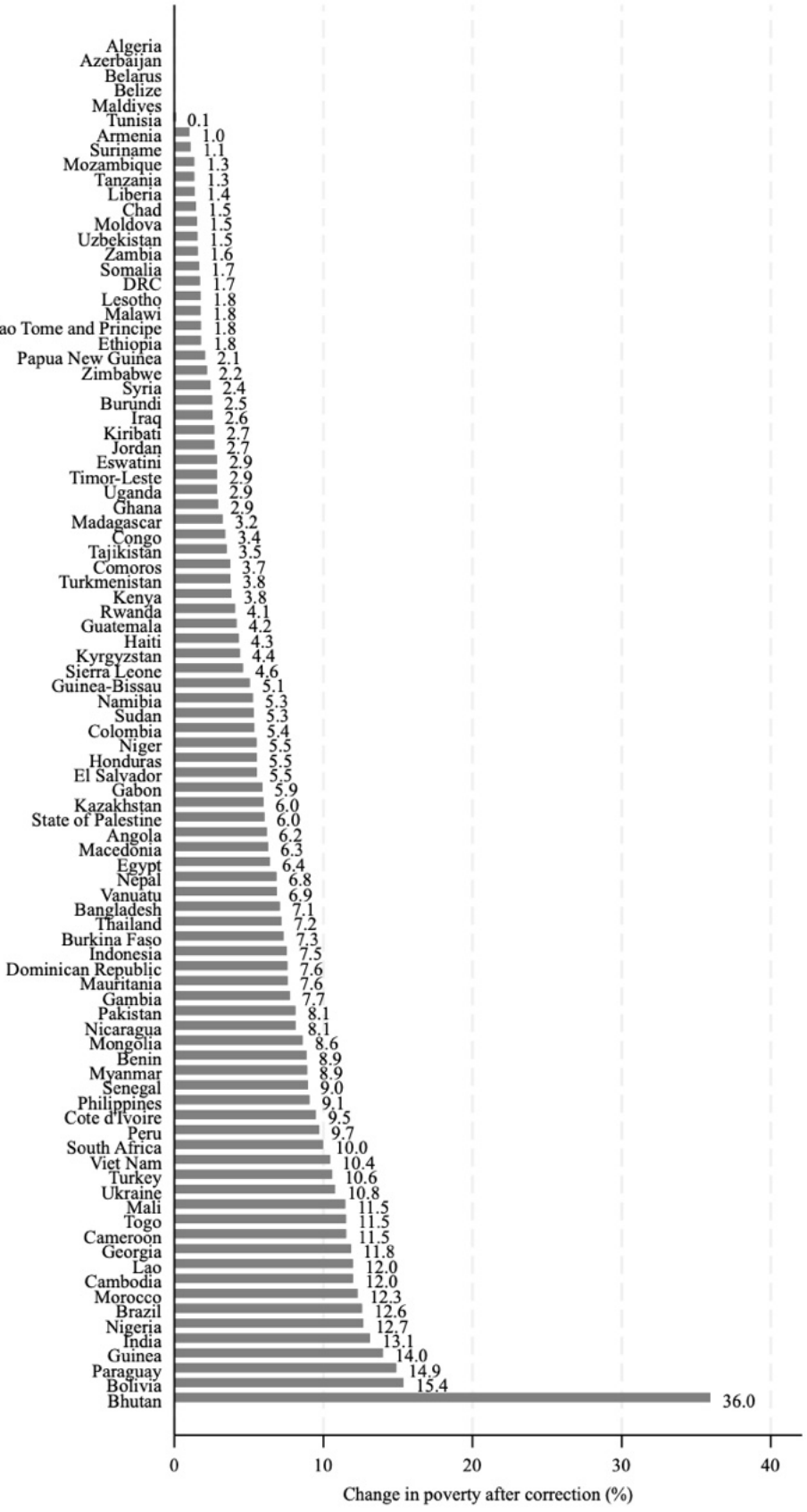


Missing poor. Table 1 and Figure 7 report, by region and for each country, the percentage-point increase in the headcount poverty rate after the mortality correction. This is the missing poor bias, $HC^C - HC$, expressed in percentage points. The bias is strictly positive for all countries in the sample by construction because the mortality gradient is positive everywhere, the correction always adds poor individuals. But its magnitude varies enormously. For a cluster of countries at the lower end (Azerbaijan, Belarus, Cambodia), the bias is negligible, below 0.5 percentage points. For a growing number of countries in the middle of the distribution, the bias lies between 2 and 8 percentage points. At the upper extreme, Bhutan stands out with a correction of 36 percentage points, followed by Bolivia (15.4), Paraguay (14.9) and Guinea (14.0). Nigeria, India and Brazil, all large and populous countries, display corrections in the 12 to 13 percentage point range.

The geographic pattern is consistent with the gradient heterogeneity documented in Section 3. African countries dominate the upper tail of the distribution, but high corrections also appear in parts of Latin America (Bolivia, Paraguay, Brazil, Peru) and South and Southeast Asia (India, Bangladesh, Indonesia). This geographic spread is important and it shows that the missing poor problem is not confined to Sub-Saharan Africa but is a pervasive feature of developing-country poverty measurement. Conversely, the relatively modest corrections in Europe and Central Asia confirm that more developed institutional environments, with better access to health care and more compressed

longevity inequality, substantially reduce the selection bias. This is something we investigate in the next section.

Figure 7: Change in poverty measures after correction for missing poor (in %)



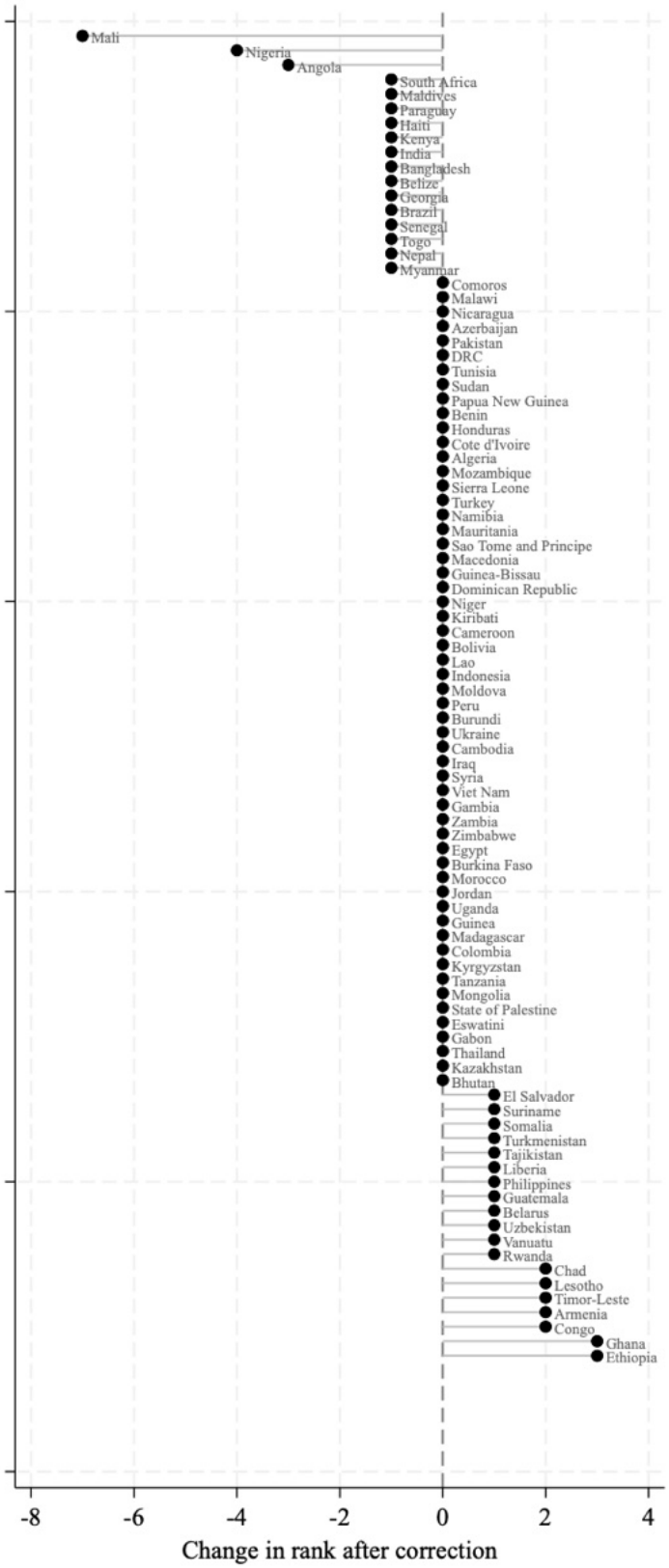
Changes in international poverty rankings. A particularly striking implication of the cor-

rection is that it can reverse the poverty ranking between countries. Figure 8 plots the change in each country's rank after the correction is applied. It is measured by its position in the cross-country ordering of poverty headcount rates. A negative value indicates that a country moves up in the poverty ranking (i.e., its corrected poverty rate is higher relative to other countries than its observed rate), while a positive value indicates the opposite.

The figure reveals that ranking reversals are widespread. Mali and Niger experience the largest upward revision, each moving approximately six to eight positions up the poverty ladder once differential mortality is accounted for. These countries have relatively moderate observed poverty rates but very steep mortality gradients, so the correction disproportionately inflates their measured poverty. Conversely, countries such as Ghana and Ethiopia move down the ranking. Their high observed poverty rates are only modestly affected by the correction because their mortality gradients, while present, are less extreme relative to the size of their poor population.

These reversals carry direct implications for the international monitoring of poverty. Rankings of countries by headcount poverty rate are routinely used to guide the allocation of aid, the prioritisation of development interventions, and the assessment of progress toward the Sustainable Development Goals. A correction that shifts countries by several positions in the global poverty ranking is not a second-order refinement. It potentially reroutes resources and attention away from countries where the mortality-selection bias is severe and toward countries where observed poverty already overstates the true burden. This finding echoes the theoretical point made in the introduction that the comparability of standard poverty measures across countries is compromised by differential mortality, and the invisible continent of uncounted poverty is not distributed proportionally across regions.

Figure 8: Change in rank after correction



5 Drivers and Mechanisms

The previous section documented that the missing poor bias varies enormously across countries, from negligible corrections in Azerbaijan or Belarus to adjustments exceeding 10 percentage points in Nigeria, India, and Bolivia. This section examines what drives this heterogeneity and provides causal estimates of the effect of health system quality on the bias and on the income-mortality gradient. Our empirical strategy follows directly from the structure of the bias derived in Section 2. Cross-country differences in the missing poor bias reflect two forces. The first is the slope of the income-mortality gradient which captures how steeply survival probabilities rise with wealth. The more strongly survival increases with income, the more conventional poverty measures understate poverty by failing to account for differential mortality. The second is the density of the income distribution around the poverty line. The bias is larger when more individuals are concentrated near the threshold at which mortality-induced changes in the population at risk translate into changes in the poverty headcount. We refer to these mechanisms as the *gradient* and *density* channels.

5.1 Empirical strategy

We examine two outcomes throughout the analysis. The first is the missing poor bias $HC^C - HC$, expressed in percentage points, which reflects the two channels jointly. The second is the income-mortality gradient $\hat{\beta}$ estimated in equation (20), which reflects the gradient channel alone. Estimating the same specification on both outcomes is what allows us to assign an association to one channel rather than the other. A covariate that shifts the bias but leaves the gradient unchanged operates through the density of the income distribution near the poverty line, whereas a covariate that shifts both operates through the steepness of the survival gradient.

Though focusing on the gradient channel only makes sense. First, the two channels are not symmetric in what they represent. The gradient records how unequally survival is distributed across the wealth distribution, whereas the density is a property of the income distribution that governs how much a given gradient translates into a headcount correction. Since the missing poor phenomenon is by construction a mortality phenomenon, the gradient carries the mechanism at the heart of this paper and the density only scales its magnitude. Second, it is the channel on which policy can act because the coverage of essential health services is an explicit object of international commitment whereas the position of the income distribution relative to the poverty line is not a direct policy lever. Third, it is the only channel for which credible identification is available. Health system development admits plausibly exogenous variation that we exploit below, whereas the determinants of the income

density near the poverty line are numerous, mutually correlated and not separable in a cross section of this size. Our design is therefore deliberately asymmetric. The density channel enters the analysis as a set of controls that hold the second determinant of the bias fixed, rather than as an object of identification in its own right.

For each outcome y_c we therefore estimate the cross-country specification

$$y_c = \mu + \gamma\,\mathrm{UHC}_c + X_c'\delta + Z_c'\theta + u_c, \tag{22}$$

where c indexes the countries of our sample, UHC_c is the gradient-channel variable whose coefficient γ is the object of interest, X_c collects the base controls and Z_c collects the density-channel controls. We report four control sets for each outcome, introducing the two components of Z_c first separately and then jointly, which allows us to assess their individual contributions and to verify that $\hat{\gamma}$ is stable across them.

The gradient-channel variable is the Universal Health Coverage (UHC) index released by the World Health Organization, which measures the coverage of essential health services across reproductive health, child health, infectious disease and service-capacity domains.[14] It is the most direct and policy-relevant measure of health system access. A low score reflects precisely the unequal access to survival-determining interventions that steepens the income-mortality gradient and enlarges the missing poor bias. As an alternative we use the communicable disease share of total deaths, defined as the fraction of deaths attributed to communicable, maternal, neonatal and nutritional causes. Communicable diseases such as malaria, tuberculosis, pneumonia and diarrhoeal illnesses are disproportionately concentrated among the poorest wealth quintiles, both because exposure to pathogens is higher in poor households and because treatment access is limited. A large communicable share steepens the gradient by construction. The two variables are collinear proxies for the same dimension of health system capacity and we never enter them jointly. We treat UHC as the primary measure because it is a positive indicator of system performance with a clear normative and policy interpretation and we verify as a robustness test in Section 5.4 that the communicable disease share delivers qualitatively identical conclusions.

The base controls X_c are log GDP per capita and the Gini coefficient. Both serve to separate the health system channel from confounders that are linked to the bias through routes unrelated to health system quality. Richer countries invest more in health infrastructure, attract better trained health workers and maintain more complete civil registration systems, all of which reduce the bias

[14] It is the focal indicator of Sustainable Development Goal 3.8.

independently of UHC. Not conditioning on income the estimate of γ would absorb this broader development effect. Income inequality in turn shapes the dispersion of health access across the wealth distribution independently of average income. A country with high inequality can record a moderate aggregate UHC score while exhibiting extreme disparities in access between its richest and poorest quintiles, steepening the gradient beyond what average coverage would predict. Conditioning on the Gini coefficient therefore ensures that γ captures universal access rather than average access. It absorbs the variation in the shape of the income distribution that would otherwise confound comparisons across countries with different degrees of inequality.

The density-channel controls Z_c are the poverty gap and social protection coverage. Even at a given gradient slope, the bias is larger in countries where many individuals are clustered just below the poverty line. A given differential in survival probability converts into a larger correction to the headcount when the threshold cuts through a dense part of the distribution. The poverty gap measures how far below the line the poor fall on average, so that a large gap indicates deeply impoverished households and a mass of the distribution concentrated at low incomes. Social protection coverage reflects the institutional capacity to smooth consumption near the threshold and therefore governs how many individuals sit just below and just above it. These variables are conceptually orthogonal to UHC_c. Conditional on health system coverage they do not affect how steeply mortality rises with income but they determine how much a given gradient matters for the bias. The two channels are additive rather than collinear and conditioning on Z_c sharpens identification without introducing multicollinearity. We merge our 92-country estimates with these variables, all measured at the country level for the most recent available year. The poverty gap is not available for Cambodia and Somalia.[15]

Estimating equation (22) by OLS does not identify γ. Health-system coverage, disease burden, income, and the missing poor bias are jointly determined. Poorer countries tend to have both weaker health systems and heavier communicable-disease burdens, which are themselves associated with a larger bias. Cross-sectional OLS therefore cannot isolate the causal effect of health-system coverage from reverse causality and correlated omitted factors. Measurement error provides an additional concern because the UHC index aggregates multiple dimensions of service coverage and is inevitably measured with noise. This potentially attenuates the OLS coefficient toward zero. We therefore instrument health-system coverage with the malaria ecology index of Kiszewski et al. (2004). This

[15]Log GDP per capita (PPP, constant 2017 international $) and the poverty gap at the $2.15/day threshold come from the World Development Indicators. The Gini coefficient is from the World Bank Poverty and Inequality Platform. The UHC service coverage index (0–100) is from the WHO Global Health Observatory. Social protection coverage (% of population) is from the ILO World Social Protection Database. The communicable disease share of total deaths (%) is from WHO Global Health Estimates (GHE 2021).

predetermined feature of the disease environment, discussed in detail in Section 5.3 below, provides exogenous variation in health-system development. The corresponding first-stage equation is

$$\mathrm{UHC}_c = \pi_0 + \pi_1 \,\mathrm{ME}_c + X_c'\lambda + Z_c'\psi + v_c, \tag{23}$$

where ME_c denotes the malaria ecology index. We first report OLS benchmarks for both outcomes and then present the first stage and the 2SLS estimates. We also subject both sets of results to a battery of robustness checks.

5.2 OLS benchmarks

Table 2 reports OLS estimates with UHC coverage as the gradient-channel variable and, respectively, the missing poor bias (columns 1–4) and the mortality gradient $\hat{\beta}$ (columns 5–8) as outcomes. Each set of four columns presents the same sequence of control sets with first base controls only (log GDP per capita and Gini coefficient), then adding the poverty gap, then adding social protection coverage without the poverty gap, and finally adding both density-channel variables jointly. This design ensures that the UHC coefficient captures the gradient channel in isolation and allows us to assess the incremental contribution of each density-channel variable.

Table 2: OLS estimates: UHC coverage, missing poor bias and mortality gradient

	Missing poor bias ($HC^C - HC$)				Mortality gradient ($\hat{\beta}$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UHC service coverage index	-0.028***	-0.031***	-0.033***	-0.035***	-0.012	-0.031	-0.059	-0.086
	(0.010)	(0.011)	(0.011)	(0.011)	(0.055)	(0.056)	(0.058)	(0.059)
Log GDP per capita PPP	-0.265**	-0.219	-0.323**	-0.298	0.421	-0.072	-0.163	-0.974
	(0.129)	(0.182)	(0.147)	(0.220)	(0.805)	(1.083)	(0.907)	(1.231)
Gini coefficient	3.153***	2.659*	3.403***	3.026*	9.008	11.280	11.498*	15.479*
	(0.965)	(1.384)	(1.014)	(1.525)	(6.299)	(8.097)	(6.331)	(8.181)
Poverty gap (%)		0.004		0.002		-0.079		-0.107
		(0.013)		(0.014)		(0.078)		(0.081)
Social protection coverage (%)			0.006	0.007			0.064*	0.075**
			(0.005)	(0.005)			(0.034)	(0.035)
Observations	92	90	92	90	92	90	92	90
R^2	0.400	0.414	0.409	0.423	0.025	0.028	0.058	0.074

Notes: Robust standard errors in parentheses. In column (5) to (8), the dependent variable is income-mortality gradient $\hat{\beta}$ rescaled $\times 10$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Poverty gap is missing for Cambodia and Somalia.

The results for the missing poor bias are robust and consistent. The UHC coverage coefficient is negative, precisely estimated, and significant at the 1 percent level across all four columns, ranging from -0.029 in the baseline (column 1) to -0.036 in the joint density specification (column 4). A 10-point increase in UHC coverage is associated with a reduction of approximately 0.30 percentage points in the missing poor bias. This estimate is stable to the inclusion of either or both density-

channel controls, indicating that the UHC-bias association does not operate through the income distribution shape. Indee conditional on UHC, neither the poverty gap nor social protection coverage is individually significant for the bias outcome. Social protection coverage is positive but not significant in both column (3) and (4), suggesting that once UHC is controlled for, the institutional capacity to smooth consumption near the poverty line does not independently explain cross-country variation in the bias. The Gini coefficient enters positively and significantly in column (1), consistent with income inequality steepening the health gradient and enlarging the bias, though it attenuates to marginal significance as density controls are added. Log GDP per capita is negative and significant only in column (1) and (3), suggesting that the income-bias correlation is primarily mediated through health system development once UHC is controlled for.

The gradient outcome (columns 5–8) presents a strikingly different pattern. The UHC coefficient is negative in all four specifications but falls short of conventional statistical significance throughout, ranging from -0.001 to -0.009. This OLS non-result is not evidence that UHC is irrelevant for health inequality. It is, rather, consistent with classical errors-in-variables attenuation. The UHC service coverage index aggregates across multiple health service domains and is measured with noise, which biases its OLS coefficient toward zero. The fact that UHC explains 40 percent of the cross-country variance in the bias ($R^2 = 0.403$ in column 1) yet predicts the gradient only weakly ($R^2 = 0.025$) reflects this divergence. The instrumental variable estimates below correct for measurement error and reveal a precisely estimated causal effect of UHC on the gradient.

5.3 Instrumental variable approach

To isolate the causal effect of health system coverage on the missing poor bias, we instrument the UHC index with the malaria ecology index of Kiszewski et al. (2004). This index measures the biological suitability of a country's environment for malaria transmission, constructed from the geographic distribution of *Anopheles* mosquito species, their vectorial capacity, and long-run temperature patterns. It is available for all countries in our sample and captures a dimension of disease risk that is determined by ecology and geography, not by current income or policy. The identifying assumption is that malaria ecology affects the missing poor bias only through its effect on health system development, conditional on log GDP per capita and income inequality. The exclusion restriction is plausible because the Kiszewski index captures entomological characteristics of the environment that predate modern health institutions; it does not directly shape the income distribution at birth, which is the channel through which income distribution affects the bias independently of the gra-

dient.[16] The index is not a measure of current malaria incidence or mortality, which are outcomes of health policy and therefore potentially endogenous. It is instead a pre-determined characteristic of geography and ecology that reflects the disease environment countries inherited before any modern public health intervention. High malaria ecology countries face a structurally more demanding disease burden that historically required, and continues to require, proportionally greater health system investment merely to maintain baseline coverage, leaving fewer resources and organisational capacity available for broader service delivery. An environment with high intrinsic suitability for malaria transmission depresses UHC coverage through persistent strain on health system capacity, a relationship confirmed by a strong first stage across all specifications.

The instrument is plausibly exogenous for two reasons. First, mosquito species composition and the climatic parameters governing parasite development are determined by geography and evolutionary history. No country can alter its malaria ecology through contemporary policy. Second, and more importantly for our identification strategy, malaria ecology has no direct effect on the shape of the income distribution near the poverty line. Countries with high malaria ecology do not mechanically have larger poverty gaps or weaker social protection systems relative to their income level. The exclusion restriction therefore holds conditional on log GDP per capita and the Gini coefficient. Malaria ecology affects the missing poor bias only through its effect on health system capacity, and not through any direct influence on where the income distribution is located relative to the poverty threshold. This distinction between the gradient channel, through which the instrument operates, and the density channel, through which it does not operate, has an empirically testable implication. Adding density-channel controls (poverty gap and social protection coverage) to the IV specification should not weaken the first stage, since these variables are orthogonal to the instrument. We verify this below and find that the Kleibergen-Paap F-statistic remains stable at approximately 18-20 across all control sets, confirming that the instrument retains its identifying power regardless of whether density-channel variables are included.

5.3.1 First-stage estimates

Before turning to the IV estimates, it is useful to verify that the IV approach is warranted in the first place. The Durbin-Wu-Hausman test of exogeneity rejects the null hypothesis that UHC coverage is exogenous at conventional significance levels in the baseline specification[17]. This confirms

[16] As a falsification check, we verify that the malaria ecology index is not significantly correlated with the lognormal dispersion parameter $\hat{\sigma}$ of the income distribution, conditional on controls. A significant correlation would suggest that the instrument affects the bias through the income distribution shape rather than exclusively through the health system channel.

[17] In the baseline estimation of Poverty bias, the endogeneity test rejects the null of exogeneity of UHC service coverage at the 5% level, with a test statistic of 6.241 and a p-value of 0.012.. In the estimation of the gradient, the

that OLS estimates of the gradient channel are biased, and that an instrumental variable approach is needed to recover the causal effect. As further support, the reduced form yields a positive and significant coefficient, confirming that the instrument has a well-defined effect on the outcome through the postulated channel before any IV rescaling is applied.

Table 3 reports the first stage under all four control specifications, and Figure 9 displays the relationship graphically as a partial scatter of UHC coverage against malaria ecology residualised on the base controls. The negative gradient is clearly visible in the scatter plot with countries in ecologically hostile malaria environments having systematically weaker UHC coverage conditional on income and inequality. Across every column of the table, the malaria ecology index is a strong and negative predictor of UHC coverage. In the baseline (column 1), a one-unit increase in the index reduces the UHC service coverage index by 0.70 points; the coefficient is essentially unchanged in columns (2) and only slightly attenuated once social protection coverage is added in column (3) and (4). This pattern reflects the long-run burden-of-disease mechanism saying that countries in ecologically hostile malaria environments historically invested less in public health infrastructure and civil registration capacity, leading to persistently weaker health systems (Acemoglu et al., 2001; Gallup et al., 1999). The Kleibergen-Paap partial F-statistic is ranging from 17.83 to 19.86 depending on specifications. All four values exceed the conventional threshold of 10 and the more stringent Stock-Yogo threshold of 16.38 for a 5 percent maximal size distortion (Stock and Yogo, 2005). This stability arises because the density-channel controls (poverty gap and social protection coverage) are orthogonal to malaria ecology. The biological suitability of an environment for malaria transmission has no direct effect on the depth of poverty or the institutional capacity for social protection, so adding these variables leaves the instrument's variation intact. The first stage is therefore strong irrespective of which density-channel controls are included.

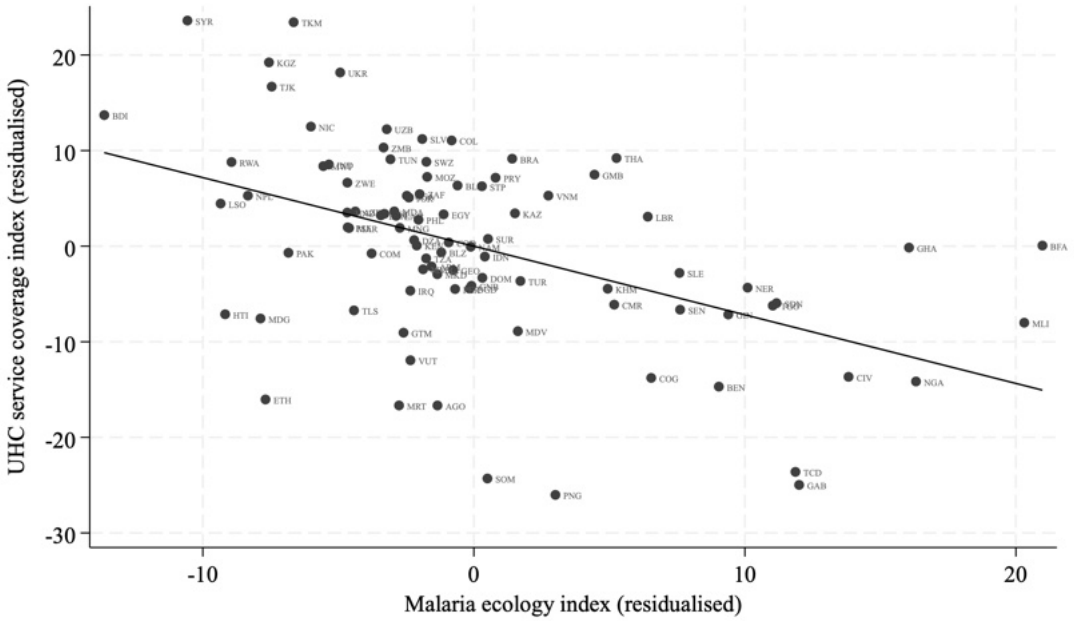
endogeneity test rejects the null of exogeneity of UHC service coverage at the 5% level, with a test statistic of 5.956 and a p-value of 0.015.

Table 3: First stage: malaria ecology index on UHC service coverage

	Dependent variable: UHC service coverage index			
	(1)	(2)	(3)	(4)
Malaria index	-0.700***	-0.698***	-0.597***	-0.604***
	(0.157)	(0.157)	(0.141)	(0.140)
Log GDP per capita PPP	8.780***	7.626***	5.223***	3.706**
	(1.272)	(1.762)	(1.431)	(1.859)
Gini coefficient	-6.679	0.415	3.260	12.637
	(10.784)	(12.724)	(8.998)	(11.904)
Poverty gap (%)		-0.131		-0.192
		(0.133)		(0.121)
Social protection coverage (%)			0.225***	0.217***
			(0.058)	(0.057)
Observations	92	90	92	90
Partial F (malaria ecology)	19.79	19.86	17.83	18.55

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Instrument: malaria ecology index (Kiszewski et al., 2004). Partial F: F-statistic from test of the exclusion of malaria ecology from the first stage. Poverty gap is missing for Cambodia and Somalia.

Figure 9: First stage: UHC coverage and malaria ecology (residualised on base controls)



Notes: Partial scatter of UHC service coverage index against malaria ecology index (Kiszewski et al., 2004), both residualised on log GDP per capita and Gini coefficient. Each point represents one country. The fitted line corresponds to the first-stage regression in column (1) of Table 3. Countries above the line have higher UHC coverage than predicted by their malaria ecology and income level; countries below have lower coverage.

5.3.2 2SLS estimates

Table 4 presents 2SLS estimates for both outcomes simultaneously, following the same eight-column structure as Table 2. The 2SLS results for the missing poor bias (columns 1–4) are strikingly

stable. The coefficient on UHC coverage ranges from −0.098 to −0.117, significant at the 1 percent level in every column. Adding the poverty gap, social protection coverage without the poverty gap, or both density-channel variables jointly leaves this estimate essentially unchanged. This triple stability; across coefficients, standard errors, and F-statistics; confirms that the causal estimate of the gradient channel is not confounded by density-channel variables. Conditional on malaria ecology variation, health system coverage and income distribution density operate through distinct pathways. The 2SLS estimates are more than three times larger in absolute value than the OLS benchmarks in Table 2, a pattern consistent with classical attenuation bias arising from measurement error in the UHC composite index. By exploiting the exogenous variation in malaria ecology, IV corrects this downward bias and reveals the true causal magnitude of health system coverage on the missing poor problem.

Table 4: 2SLS estimates: missing poor bias and income-mortality gradient

	Missing poor bias ($HC^C - HC$)				Mortality gradient ($\hat{\beta}$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UHC service coverage index	-0.098***	-0.098***	-0.117***	-0.115***	-0.291**	-0.282**	-0.392**	-0.375**
	(0.034)	(0.034)	(0.040)	(0.040)	(0.135)	(0.135)	(0.160)	(0.156)
Log GDP per capita PPP	0.561	0.505	0.267	0.141	3.720**	2.636	2.167	0.629
	(0.411)	(0.420)	(0.350)	(0.367)	(1.713)	(1.793)	(1.479)	(1.602)
Gini coefficient	2.347*	2.368	3.511***	3.915**	5.787	10.195	11.927*	18.723**
	(1.328)	(1.622)	(1.178)	(1.566)	(7.184)	(9.100)	(6.825)	(8.866)
Poverty gap (%)		-0.003		-0.013		-0.108		-0.162*
		(0.014)		(0.014)		(0.085)		(0.086)
Social protection coverage (%)			0.029**	0.027**			0.154***	0.151***
			(0.012)	(0.011)			(0.055)	(0.051)
Observations	92	90	92	90	92	90	92	90
Kleibergen-Paap F	19.79	19.86	17.83	18.55	19.79	19.86	17.83	18.55

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In column (5) to (8), the dependent variable is income-mortality gradient $\hat{\beta}$ rescaled ×10. The instrument is themalaria ecology index (Kiszewski et al., 2004). F-statistic from test of the exclusion of malaria ecology from the first stage. Poverty gap is missing for Cambodia and Somalia.

The gradient outcome (columns 5–8) delivers the same message with an important additional insight. As documented in Table 2, the OLS coefficient on UHC coverage is very low and not significant. The 2SLS estimates are qualitatively different and across all four columns, the coefficient ranges from −0.026 to −0.035 and is significant at the 5 percent level. The contrast between the flat OLS and the significant 2SLS estimates is itself a substantive finding. It indicates that measurement error in the UHC composite index attenuates the OLS gradient toward zero, so that the OLS coefficient −0.002 understates the true causal effect by an order of magnitude. Correcting for this attenuation through IV reveals a meaningful causal effect on health inequality. Taken together with the bias results, this confirms that health system coverage operates on the missing poor bias through the mortality gradient channel. Countries with weaker health systems exhibit steeper income-mortality

gradients, and those gradients translate directly into a larger missing poor bias. Notably, social protection coverage is significant but does not weaken the IV estimate, confirming that it captures a complementary dimension of poverty distribution density rather than health system quality.

5.4 Robustness checks

We complement the main analysis with several robustness tests applied to both outcomes. The previous estimates were obtained using the malaria ecology index as the instrument, measuring health system quality with the UHC service coverage index, estimating the model by 2SLS, and excluding region fixed effects from the baseline specification. We therefore examine whether the causal effects on the missing poor bias and the mortality gradient are sensitive to the scale of the instrument, to the choice of health proxy, to the estimator, and to the inclusion of regional fixed effects. Results for the bias are in Table 5; the corresponding results for the mortality gradient are in Table 6. Column (1) in each table report the IV estimates obtained in columns (4) and (8) of Table 4.

Instrument scale invariance. A concern with the Kiszewski et al. index is that its numerical scale is not uniquely defined, as different aggregation methods across mosquito species can yield indices expressed on different magnitudes. Column (2) addresses this by standardising the malaria ecology index to mean zero and unit standard deviation before using it as an instrument. For both outcomes, the point estimate, standard error, and Kleibergen-Paap F-statistic are all identical to column (1). The results are therefore entirely invariant to the choice of scale for the instrument, ruling out any concern that the magnitude of our estimates is driven by the arbitrary units of the Kiszewski index.

Alternative health proxy. One may worry that the UHC service coverage index captures a particular and potentially noisy composite of health services, and that the result would not hold for an independent measure of health system performance. Columns (3) and (4) address this concern by replacing UHC coverage with the communicable disease share of mortality, an entirely distinct variable constructed from cause-of-death registries rather than service coverage surveys. Column (3) shows the OLS benchmark: countries with a higher communicable disease burden exhibit a significantly larger missing poor bias and a significantly steeper income-mortality gradient. Column (4) instruments the communicable disease share with malaria ecology. The Kleibergen-Paap F-statistic rises to approximately 45, the strongest first stage in either table, reflecting the tight biological link between malaria ecology and the communicable disease burden. The 2SLS coefficients are large and significant for both outcomes. Crucially, the direction, significance, and order of magnitude of the

effects are the same as in Table 4, establishing that the main results do not depend on the specific construction of the UHC index. The stronger first stage for communicable disease also provides independent support for the exclusion restriction: the instrument appears to operate through health system quality rather than through any direct effect on the income distribution.

LIML estimator. In exactly identified models, 2SLS can exhibit finite-sample median bias. Column (5) uses the Limited Information Maximum Likelihood (LIML) estimator, which has better finite-sample properties and is robust to weak-instrument bias. Because our model has one endogenous variable and one instrument, LIML and 2SLS are algebraically equivalent under exact identification, so the estimates are necessarily identical to column (1) for both outcomes. This confirms that neither result is generated by estimator-specific bias.

Region fixed effects. One may worry that the main results reflect unobserved regional characteristics, such as colonial history, governance quality, or disease ecology beyond malaria, that are correlated with both UHC and the outcomes. Column (6) adds World Bank region fixed effects to the preferred specification. For both the bias and the gradient, the coefficient on UHC remains negative and of similar direction. However, the Kleibergen-Paap F-statistic falls well below the Stock-Yogo threshold of 16.38 in both equations, because region dummies absorb the cross-regional variation in malaria ecology on which identification relies. The instrument does not have sufficient within-region variation to support reliable 2SLS inference once region effects are absorbed. This is not an artefact of stripping controls to preserve the first stage; the weak first stage reflects a genuine limitation of the identification strategy when regional confounders are partialled out. The direction of the coefficients is fully consistent with the main results; it is the precision of the first stage, not the sign of the effects, that changes.

Taken together, these robustness tests confirm the main findings for both outcomes. Every specification with a strong first stage recovers a large, negative, and statistically significant causal effect of health system quality on the missing poor bias and on the income-mortality gradient.

6 Concluding remarks

Since the early stages of economic analysis, it has been widely acknowledged that, in a pure market economy, extreme poverty gives rise to population adjustment mechanisms that reduce the population size. That aspect of pure market economies was well underlined by, among others, Smith (1776), through his theory of the natural wage, and by Malthus (1798), through his theory of positive population checks. However, despite these early analyses of how deprivation leads to excess mortality

Table 5: Robustness: IV estimates of missing poor bias

	(1) Baseline	(2) Std. instr.	(3) Comm. OLS	(4) Comm. IV	(5) LIML	(6) Region FE
UHC service coverage index	-0.115***	-0.115***			-0.115***	-0.174*
	(0.040)	(0.040)			(0.040)	(0.102)
Communicable disease share of deaths (%)			0.039***	0.061***		
			(0.011)	(0.016)		
Log GDP per capita PPP	0.141	0.141	-0.186	-0.018	0.141	0.220
	(0.367)	(0.367)	(0.220)	(0.219)	(0.367)	(0.477)
Gini coefficient	3.915**	3.915**	1.099	0.265	3.915**	6.837
	(1.566)	(1.566)	(1.504)	(1.607)	(1.566)	(4.909)
Poverty gap (%)	-0.013	-0.013	-0.008	-0.017	-0.013	-0.018
	(0.014)	(0.014)	(0.011)	(0.012)	(0.014)	(0.019)
Observations	90	90	90	90	90	90
Kleibergen-Paap F	18.55	18.55	.	46.44	18.55	3.82

Notes: Dependent variable is missing poor bias in percentage points. Column (1) presents the baseline 2SLS estimation. Column (2) usesmalaria ecology standardised to mean 0 and SD 1 as an instrument. Columns (3)–(4) replaces UHC coverage by thecommunicable disease share of deaths; column (3) is OLS, column (4) is 2SLS. In column (5), 2SLS estimator is replaced LIML estimator. Column (6) adds World Bank region fixed effects. Poverty gap is missing for Cambodia and Somalia.Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Robustness: IV estimates of the mortality gradient

	(1) Baseline	(2) Std. instr.	(3) Comm. OLS	(4) Comm. IV	(5) LIML	(6) Region FE
UHC service coverage index	-0.375**	-0.375**			-0.375**	-0.741*
	(0.156)	(0.156)			(0.156)	(0.435)
Communicable disease share of deaths (%)			0.096*	0.198***		
			(0.051)	(0.067)		
Log GDP per capita PPP	0.629	0.629	-0.694	0.109	0.629	0.685
	(1.602)	(1.602)	(1.235)	(1.210)	(1.602)	(2.201)
Gini coefficient	18.723**	18.723**	10.765	6.780	18.723**	28.432
	(8.866)	(8.866)	(8.153)	(8.249)	(8.866)	(24.138)
Poverty gap (%)	-0.162*	-0.162*	-0.131	-0.174*	-0.162*	-0.161
	(0.086)	(0.086)	(0.084)	(0.089)	(0.086)	(0.105)
Observations	90	90	90	90	90	90
Kleibergen-Paap F	18.55	18.55	.	46.44	18.55	3.82

Notes: Dependent variable is income-mortality gradient $\hat{\beta}$ (rescaled $\times 10$). Column (1) presents the baseline 2SLS estimation. Column (2) usesmalaria ecology standardised to mean 0 and SD 1 as an instrument. Columns (3)–(4) replaces UHC coverage by thecommunicable disease share of deaths; column (3) is OLS, column (4) is 2SLS. In column (5), 2SLS estimator is replaced LIML estimator. Column (6) adds World Bank region fixed effects. Poverty gap is missing for Cambodia and Somalia. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

among the poor, it is still the case, in the 21st century, that standard measures of poverty, that is, headcount poverty rates, are polluted by income-based adjustment mechanisms, which limit the informational content of these measures, and, more seriously, question their comparability. Indeed, standard headcount poverty rates tend to go down when the survival conditions faced by the poor worsen, and they tend also to decrease when the survival conditions of the non-poor improve, whereas the living conditions faced by the poor are left unchanged. These two paradoxical features of standard headcount poverty rates tend to question their adequacy as measures of the deprivation phenomenon.

The present paper proposed to quantify the missing poor phenomenon, by comparing the standard headcount poverty rate with adjusted headcount poverty rates computed by supposing that all income classes face the survival conditions of the top income class. By construction, the adjusted headcount poverty rate is not only invariant to changes in population size (scale invariance), but also to changes in income-specific survival conditions (selection invariance). As such, this adjusted poverty rate constitutes an appealing benchmark to quantify the extent to which standard headcount poverty rate suffer from selection biases due to income-specific survival conditions.

Our calculations reveal that the missing poor bias is far from a marginal phenomenon: aggregated across the 92 countries of our sample (representing more than 4.5 billion people), the number of missing poor persons exceeds 116 million. This number admits a simple economic interpretation: provided all people would have faced the survival conditions of the top income class prevailing in their country, there would have been more than 116 million additional people counted as poor, but who were not counted as poor because of a premature death. Our explorations thus reveal the existence of a kind of invisible continent of uncounted poor persons.

A second important finding of this paper lies in the strong heterogeneity observed across countries: whereas the missing poor bias is quantitatively small in some economies, it turns out to be much larger in other countries. The mechanisms behind this heterogeneity are twofold. First, the strength of the income-mortality gradient varies a lot across countries; second, the form of income distribution varies also across countries, with a more or less high mass of people just below the poverty line. These two features imply that adding the missing persons within the adjusted headcount poverty rate has quantitative implications that vary a lot across countries. This heterogeneity tends to question the comparability of standard headcount poverty measures. Indeed, if some countries suffer a lot from the missing poor bias, whereas others do not, it follows that the international ranking of countries in terms of measured poverty may not fully capture the international ranking of the actual deprivations faced by these various populations.

A third important finding concerns the causal mechanisms behind this heterogeneity. Section 5

shows that health system coverage is a causal determinant of cross-country variation in the bias, operating through the income-mortality gradient channel. Using the UHC service coverage index as the primary measure of health system performance and instrumenting it with the malaria ecology index of Kiszewski et al. (2004), we obtain IV estimates indicating that a ten-point improvement in UHC coverage reduces the missing poor bias by approximately one percentage point, with estimates ranging from -0.098 to -0.117 across specifications. These magnitudes are roughly three times larger than their OLS counterparts, consistent with measurement error in the UHC composite index attenuating the cross-sectional coefficient toward zero. The IV further reveals a statistically significant causal effect on the income-mortality gradient itself, confirming that the mechanism runs through health inequality rather than through any confounding association between income and poverty measurement. These findings carry direct implications for the monitoring of development goals. Countries with weak health systems not only exhibit higher actual deprivation but also suffer from the largest downward biases in their official poverty statistics. Progress toward SDG 3.8 (universal health coverage) therefore yields a second dividend beyond the direct reduction in mortality: it corrects the measurement distortion that causes poverty to be systematically underestimated in the countries where the problem is most acute.

Finally, a few words should be said about the potential policy implications of our results. As it is widely acknowledged since Desrosières (1993), social statistics and social policies have been strongly linked to each other since their birth at the time of the British Political Arithmetics (late 17th century). Social policies can only be justified and evaluated provided there exist accurate measures of the 'social diseases' to be cured/monitored by means of these policies. In turn, social statistics draw their existence and legitimacy from the policies that they allow to implement. In the light of these strong interdependencies between social policies and social statistics, our findings can have massive implications regarding the assessment and design of policies aimed at fighting poverty. Indeed, making poverty measures 'selection-free' will also allow policy-makers to have a more precise quantification of the actual patterns of deprivation, without being misguided, in their policy assessments and policy design, by poverty statistics that suffer from (invisible) income-based selection processes. Once the invisible continent of the uncounted poor appears on the dashboard, it is the whole pursuit of development goals that is to be reassessed and, possibly, reoriented.

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A Appendix

A Appendix

A.1 Primary data

Table A.1: Life expectancy by wealth quintile (years)

Country	Q1	Q2	Q3	Q4	Q5
Albania	75,7	79,9	81,0	78,2	78,4
Algeria	70,9	72,9	76,9	73,2	75,2
Angola	54,8	54,7	55,5	58,3	62,0
Armenia	74,7	72,5	78,2	76,8	75,3
Azerbaijan	64,3	64,7	67,0	65,0	72,4
Bangladesh	61,4	62,5	63,7	65,2	68,3
Belarus	73,1	79,3	70,8	75,9	80,5
Belize	72,1	82,3	70,7	79,5	85,8
Benin	55,7	56,0	56,0	59,3	64,1
Bhutan	59,9	68,4	68,2	71,4	74,0
Bolivia	62,3	65,5	68,5	70,5	77,8
Brazil	67,4	72,0	79,0	81,6	83,3
Burkina Faso	50,7	49,5	51,9	52,9	59,1
Burundi	54,6	57,3	57,0	59,1	63,5
Cambodia	60,6	63,2	63,3	66,6	74,0
Cameroon	52,0	54,8	57,3	61,2	65,0
CAR	50,7	52,4	52,8	59,8	62,8
Chad	53,8	48,6	48,2	48,8	52,1
Colombia	71,5	73,1	73,4	76,7	77,6
Comoros	62,1	64,6	64,4	66,9	67,8
Congo	62,3	62,1	63,0	65,7	66,6
Cote d'Ivoire	52,6	54,0	57,3	57,5	62,6
DRC	58,3	59,3	60,7	62,1	69,5
Dominican Republic	67,8	68,9	70,3	71,9	75,6
Egypt	65,7	68,7	69,3	70,3	73,5
El Salvador	71,8	74,1	75,4	83,2	77,9
Equatorial Guinea	44,6	49,1	49,4	50,9	45,8
Eswatini	57,6	61,6	62,5	60,6	64,7
Ethiopia	59,5	59,6	56,6	56,8	61,5
Gabon	64,5	63,0	64,3	66,2	68,7
Gambia	65,4	67,5	66,1	67,7	74,8
Georgia	72,1	66,6	71,9	76,1	80,3
Ghana	60,8	63,7	63,1	65,8	66,1
Guatemala	66,4	65,9	66,8	68,2	70,2
Guinea	53,3	54,2	56,5	58,9	65,0
Guinea-Bissau	55,0	53,0	56,1	58,9	60,1
Guyana	69,5	66,8	68,9	71,1	68,6

Table A.1: Life expectancy by wealth quintile (years)

Country	Q1	Q2	Q3	Q4	Q5
Haiti	58,4	59,3	60,0	60,9	64,6
Honduras	69,0	71,5	71,7	74,0	76,5
India	58,4	59,7	62,7	65,4	70,0
Indonesia	66,3	70,0	69,9	72,4	75,5
Iraq	71,0	71,6	72,4	72,2	74,0
Jordan	71,9	72,8	73,8	74,1	75,2
Kazakhstan	69,3	70,1	71,2	72,4	75,5
Kenya	59,5	61,8	63,3	65,1	67,0
Kiribati	62,4	68,2	65,5	66,0	68,1
Kyrgyzstan	71,1	70,2	72,5	73,1	75,1
Lao	60,8	62,4	63,7	67,9	72,9
Lesotho	62,4	62,6	62,0	61,9	65,1
Liberia	57,2	58,4	57,2	58,2	59,2
Madagascar	60,6	60,0	60,2	63,4	68,7
Malawi	57,3	55,5	58,1	57,6	62,5
Maldives	77,5	74,4	80,5	74,1	77,9
Mali	50,3	49,8	50,6	53,2	62,1
Mauritania	60,6	63,7	65,5	68,4	69,3
Mongolia	65,8	66,8	68,5	72,4	73,8
Morocco	68,2	68,8	72,9	75,4	80,6
Mozambique	54,2	54,1	55,7	56,2	59,8
Myanmar	64,9	64,3	66,0	71,8	72,3
Namibia	70,8	69,2	72,4	71,7	76,9
Nepal	63,5	63,7	64,6	66,4	69,5
Nicaragua	67,3	66,9	68,5	70,5	74,8
Niger	47,5	41,4	45,4	43,6	53,6
Nigeria	49,7	49,8	53,3	58,2	65,1
Pakistan	58,9	58,7	60,6	63,4	66,4
Papua New Guinea	66,6	68,1	69,8	70,1	71,7
Paraguay	70,6	69,5	70,0	73,3	83,6
Peru	73,5	74,7	78,2	81,9	84,4
Philippines	66,4	68,5	70,6	72,3	76,4
Moldova	76,7	77,9	79,0	85,3	78,0
Macedonia	74,3	79,5	78,8	89,9	82,3
Rwanda	56,5	57,4	58,6	58,1	62,5
Sao Tome and P.	63,9	67,4	65,4	68,0	67,1
Senegal	61,4	63,3	65,2	67,6	71,9
Serbia	80,9	87,5	87,1	82,8	73,7
Sierra Leone	52,2	53,9	54,5	51,9	59,5
Somalia	58,4	53,6	57,2	56,8	58,5
South Africa	60,9	64,5	68,7	70,0	76,1
State of Palestine	73,4	73,2	73,8	74,7	79,4
Sudan	67,2	65,8	67,3	68,8	71,7
Suriname	74,7	77,3	76,1	72,4	77,2

Table A.1: Life expectancy by wealth quintile (years)

Country	Q1	Q2	Q3	Q4	Q5
Syria	75,4	74,7	75,5	77,5	77,8
Tajikistan	64,9	65,4	66,6	69,5	68,2
Thailand	81,2	84,6	91,3	90,2	92,7
Timor-Leste	66,6	66,7	67,1	68,5	71,1
Togo	55,9	56,4	59,1	64,2	69,1
Tunisia	80,7	79,4	74,4	77,1	79,0
Turkey	64,3	67,6	70,0	71,8	76,0
Turkmenistan	69,2	70,3	71,4	74,3	72,7
Uganda	58,5	59,6	60,9	60,0	65,2
Ukraine	72,4	75,3	81,0	84,6	85,3
Tanzania	61,3	59,5	60,6	61,3	61,6
Uzbekistan	68,1	67,4	67,6	69,5	68,8
Vanuatu	67,6	69,5	69,4	67,2	77,1
Viet Nam	70,3	74,7	76,9	80,7	83,2
Zambia	57,4	57,1	57,9	57,9	61,9
Zimbabwe	63,2	63,7	63,5	64,8	67,1

Table A.2: Income levels by decile (GDPpc international $)

Country	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Albania	6018,1	8927,2	11066,0	13095,0	15232,2	17639,1	20530,1	24347,7	30350,1	47756,5
Algeria	4240,5	5840,8	7252,9	8598,9	9972,0	11473,4	13257,8	15643,8	19586,2	36401,6
Angola	1019,6	1855,6	2555,8	3288,7	4136,7	5104,2	6354,8	8187,5	11171,2	26086,0
Armenia	6722,0	9363,5	11093,6	12793,6	14601,6	16561,8	18897,1	22057,4	27259,9	50306,7
Azerbaijan	7341,0	9621,3	11138,1	12560,7	13936,9	15543,7	17572,4	20398,0	25130,7	45043,3
Bangladesh	2903,9	3807,1	4462,1	5080,1	5721,5	6440,3	7319,9	8532,7	10605,1	19102,7
Belarus	8493,8	12056,1	14428,9	16601,2	18742,3	21077,4	23784,8	27286,9	32704,9	50330,2
Belize	983,4	2359,0	3306,0	4233,2	5321,9	6682,6	8564,1	11203,4	16368,4	52876,7
Benin	999,2	1509,1	1969,5	2341,0	2746,6	3225,7	3842,4	4714,2	6208,6	13018,3
Bhutan	3752,2	5308,9	6522,0	7754,4	9138,8	10733,7	12783,9	15451,4	19923,6	36584,7
Bolivia	2855,5	4040,2	4963,4	5901,4	6954,9	8168,7	9729,0	11759,0	15162,5	27842,2
Brazil	1640,8	3492,8	5030,5	6711,1	8660,4	11074,3	14262,7	19147,8	28860,0	79396,0
Burkina Faso	673,8	968,0	1180,4	1385,3	1612,0	1898,6	2268,2	2820,7	3834,4	8857,9
Burundi	247,4	353,5	433,7	512,2	595,7	692,1	809,3	976,6	1265,7	2478,4
Cambodia	2003,0	2726,5	3205,8	3664,6	4151,2	4715,4	5415,0	6359,6	7873,7	13436,9
Cameroon	991,4	1472,1	1860,4	2277,0	2768,0	3354,8	4109,0	5201,9	7077,9	14868,0
Chad	415,8	632,8	796,8	965,1	1162,4	1370,6	1623,4	1986,4	2626,2	5106,3
Colombia	2196,9	4676,9	6654,7	8645,9	10909,5	13678,6	17360,2	22811,2	33041,2	89540,4
Comoros	603,5	1022,7	1381,0	1752,2	2123,7	2606,7	3283,6	4141,2	5749,5	15673,2
Congo	763,2	1207,4	1613,4	2036,5	2531,2	3111,5	3882,7	5014,3	6981,3	16209,1
Cote d'Ivoire	1613,2	2492,1	3140,7	3769,6	4448,3	5284,0	6298,4	7776,8	10306,1	20275,5
DRC	354,5	573,3	738,8	902,3	1078,1	1287,6	1567,9	1961,4	2661,7	5577,4
Dominican Republic	4023,6	6794,6	8995,5	11235,3	13726,1	16718,3	20565,9	26110,7	36131,8	84109,1
Egypt	5980,8	7855,4	9129,4	10307,3	11542,1	12934,0	14648,0	17002,6	21020,5	40539,9
El Salvador	1758,5	3313,0	4526,6	5728,7	7015,6	8512,1	10424,7	13108,7	17886,8	38706,4

Table A.2: Income levels by decile (GDPpc international $)

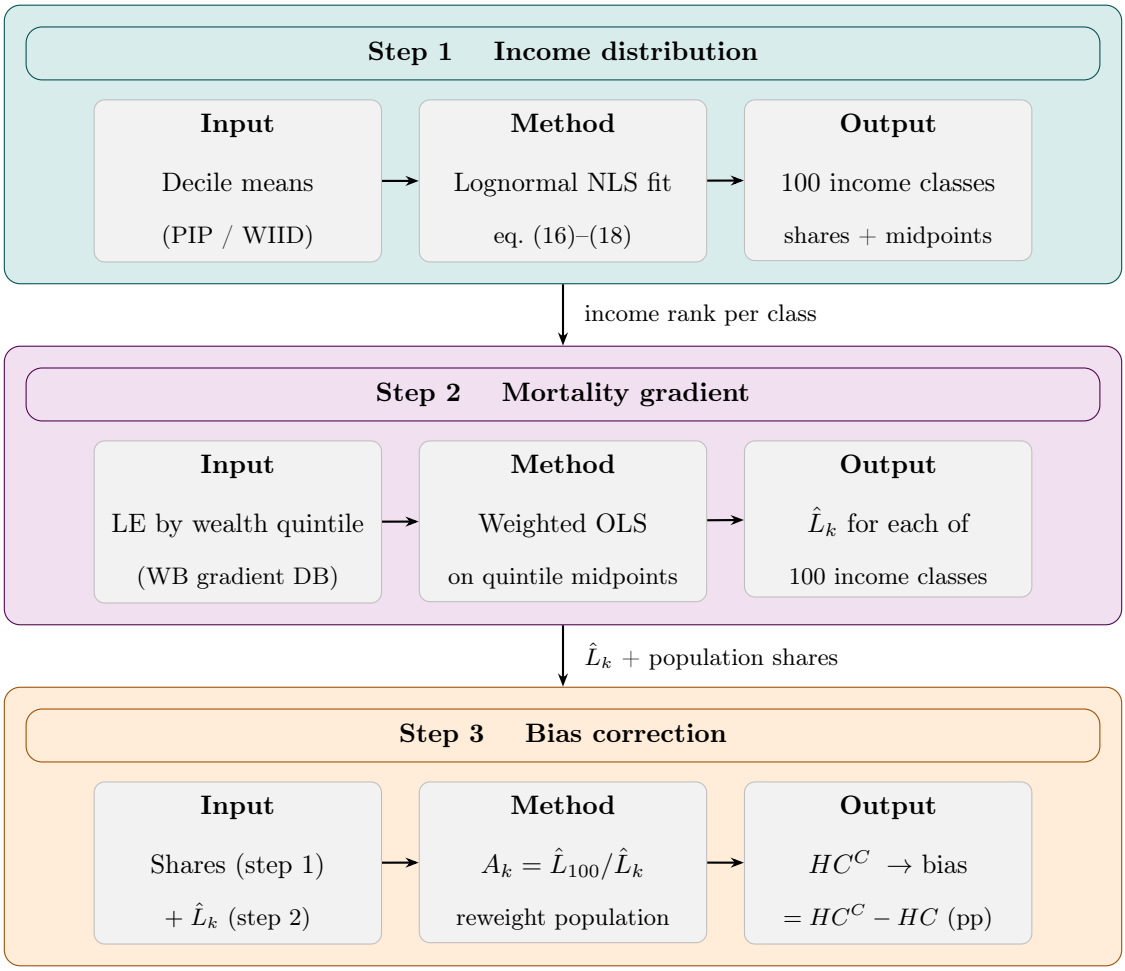
Country	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Equatorial Guinea	4756,0	6919,3	8554,9	10175,4	11971,0	14138,5	16743,5	20448,1	26755,3	55745,4
Eswatini	1495,4	2455,3	3268,7	4138,7	5166,9	6497,9	8364,7	11268,3	17158,6	47180,9
Ethiopia	949,3	1336,6	1602,0	1846,3	2110,9	2392,1	2712,3	3159,6	3927,8	8088,2
Gabon	3715,4	6053,3	7740,6	9472,3	11333,7	13450,3	16264,6	20029,0	26477,8	50112,8
Gambia	554,9	880,5	1121,3	1351,1	1611,5	1931,1	2335,7	2901,6	3851,1	8426,0
Georgia	4569,4	7796,2	10126,5	12353,5	14707,8	17347,0	20568,1	24876,6	31813,5	57562,2
Ghana	1484,3	2363,5	3062,0	3763,2	4509,3	5346,1	6412,2	7890,3	10309,2	19590,7
Guatemala	1218,6	2263,2	3249,0	4301,5	5530,4	6976,7	8870,6	11658,8	16828,8	47320,1
Guinea	754,6	1178,8	1505,1	1830,9	2193,1	2618,5	3156,2	3897,5	5112,2	9633,8
Guinea-Bissau	591,4	860,4	1063,8	1265,3	1488,6	1758,1	2082,1	2542,7	3327,1	6932,0
Guyana	4601,7	13145,7	18363,8	22920,8	27651,7	33407,2	40262,8	49388,2	66173,6	144983,5
Haiti	363,2	723,0	1042,0	1371,3	1737,7	2166,2	2756,9	3616,9	5262,6	14022,0
Honduras	668,7	1356,7	1994,0	2712,4	3534,2	4520,0	5824,5	7711,5	11192,0	27919,2
India	2920,9	3965,7	4723,3	5450,8	6216,4	7094,7	8193,7	9730,9	12380,3	23327,0
Indonesia	5075,6	6779,2	8041,6	9318,0	10722,0	12364,9	14421,5	17256,3	21935,5	40663,3
Iraq	4142,2	5673,2	6722,7	7687,4	8712,7	9840,8	11204,1	13039,1	15918,0	25713,9
Jordan	3567,7	4870,2	5915,9	6943,9	8037,9	9286,7	10843,3	13064,4	16904,7	32664,5
Kazakhstan	11563,6	15729,6	18508,2	21189,6	24089,6	27451,6	31592,8	37114,5	45844,3	75117,0
Kenya	1279,3	1996,2	2528,8	3057,3	3644,8	4342,7	5238,3	6534,3	8755,0	20281,5
Kiribati	779,3	1119,7	1370,8	1593,1	1833,0	2093,6	2409,8	2836,0	3457,1	6162,7
Kyrgyzstan	2239,9	3049,0	3585,0	4098,1	4642,2	5273,1	6055,6	7111,9	8805,0	15026,3
Lao	2239,9	3049,0	3585,0	4098,1	4642,2	5273,1	6055,6	7111,9	8805,0	15026,3
Lesotho	275,7	520,3	761,3	1025,5	1353,4	1769,0	2321,9	3114,0	4536,2	10784,5
Liberia	443,6	679,7	847,3	1011,1	1187,6	1364,5	1584,0	1907,2	2417,6	4262,3
Madagascar	399,4	626,4	795,1	963,1	1147,0	1364,9	1640,7	2045,1	2775,4	5989,5
Malawi	420,7	607,1	742,7	878,4	1026,0	1202,8	1429,4	1754,2	2325,8	6939,1
Maldives	7753,5	11270,1	13827,3	16196,4	18673,1	21496,2	24746,5	29157,4	36994,8	71130,8
Mali	691,4	1005,3	1229,6	1458,9	1705,6	2006,1	2420,7	3007,7	3987,9	7676,2
Mauritania	1544,6	2432,9	3081,6	3733,4	4431,4	5235,3	6227,2	7557,4	9747,2	18966,9
Mongolia	4537,8	6519,3	8010,9	9439,0	10970,3	12698,7	14732,8	17480,6	21886,0	36327,7
Morocco	2548,1	3726,1	4626,3	5504,0	6489,9	7640,0	9053,4	11077,8	14499,9	30311,1
Mozambique	258,2	431,9	559,4	686,0	826,8	992,6	1213,5	1541,0	2160,4	6103,5
Myanmar	1686,1	2376,8	2833,7	3263,4	3714,7	4229,9	4863,1	5726,7	7140,6	14362,4
Namibia	1299,5	2178,8	2873,4	3620,4	4541,5	5772,3	7677,4	10790,9	17413,0	59145,9
Nepal	1595,5	2150,4	2556,7	2956,9	3407,5	3903,3	4529,0	5387,0	6921,9	13857,9
Nicaragua	1178,8	1990,3	2648,6	3319,1	4064,5	4939,0	6066,4	7749,8	10590,6	26223,6
Niger	467,6	662,0	792,4	924,3	1063,2	1226,5	1427,3	1716,6	2222,8	4552,6
Nigeria	1371,3	2113,2	2723,3	3354,9	4040,1	4856,4	5878,2	7307,7	9599,8	17377,5
Pakistan	2567,5	3342,5	3861,9	4354,3	4876,4	5471,9	6199,4	7220,9	8952,5	16662,8
Papua New Guinea	830,1	1371,5	1841,7	2314,6	2853,7	3496,9	4302,9	5413,6	7392,3	14510,6
Paraguay	2284,4	4158,5	5747,7	7349,9	9143,2	11271,3	14052,1	18006,8	24994,9	62817,4
Peru	2205,5	4096,3	5778,9	7498,0	9364,3	11526,6	14191,5	17900,1	24222,4	53741,5
Philippines	2514,8	3563,6	4413,9	5316,5	6360,3	7644,0	9340,3	11805,3	16151,3	34255,4
Moldova	1544,6	2432,9	3081,6	3733,4	4431,4	5235,3	6227,2	7557,4	9747,2	18966,9

Table A.2: Income levels by decile (GDPpc international $)

Country	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Macedonia	4102,4	7862,5	10750,9	13394,3	16129,5	19130,7	22668,9	27245,1	34340,5	57419,8
Rwanda	710,0	1014,9	1249,4	1481,2	1727,4	2016,1	2397,2	2953,9	4015,8	10366,0
Sao Tome and Principe	710,0	1014,9	1249,4	1481,2	1727,4	2016,1	2397,2	2953,9	4015,8	10366,0
Senegal	1045,7	1551,6	1936,4	2332,5	2775,2	3292,9	3951,3	4881,5	6450,5	13886,1
Serbia	6544,9	11151,4	14206,9	16996,6	19745,6	22719,6	26265,0	30846,9	37970,5	64171,0
Sierra Leone	597,2	844,1	1012,4	1179,0	1356,6	1573,2	1848,5	2247,4	2964,8	5685,6
Somalia	271,1	510,8	697,9	883,2	1081,6	1312,3	1607,1	2020,9	2757,6	5967,2
South Africa	1678,9	2575,4	3453,6	4488,7	5826,5	7673,6	10578,8	15772,3	27861,2	79295,3
State of Palestine	2042,7	3016,9	3670,8	4343,2	5037,5	5835,3	6836,0	8200,2	10401,3	18206,3
Sudan	1225,9	1863,3	2292,9	2708,6	3154,5	3673,3	4288,1	5096,8	6386,0	11484,9
Suriname	1958,7	4227,9	6691,7	8757,5	11143,3	13278,9	16128,8	21226,4	30168,8	64152,7
Syria	1958,7	4227,9	6691,7	8757,5	11143,3	13278,9	16128,8	21226,4	30168,8	64152,7
Tajikistan	1520,7	2327,8	2838,5	3319,7	3826,9	4388,1	5054,4	5913,0	7365,4	12312,9
Thailand	5707,6	7939,1	9700,4	11552,1	13693,2	16286,3	19681,4	24478,4	32568,5	65184,1
Timor-Leste	1742,5	2329,2	2769,5	3185,4	3612,3	4106,7	4725,4	5559,8	6887,6	11655,3
Togo	589,2	893,0	1141,0	1398,7	1686,8	2022,8	2478,5	3128,4	4280,3	8398,9
Tunisia	3221,6	4840,1	6180,8	7481,5	8868,6	10457,0	12392,6	15030,9	19419,3	36944,1
Turkey	8189,7	13347,9	17529,1	21605,1	25968,2	31002,3	37241,4	46041,6	60835,7	121790,6
Turkmenistan	3756,3	5774,5	7303,8	8796,0	10412,8	12281,1	14955,2	18764,4	24976,3	49264,2
Uganda	648,6	976,4	1222,9	1467,9	1736,7	2050,6	2454,0	3039,7	4084,0	9250,4
Ukraine	4940,3	6841,5	8091,8	9253,5	10430,9	11711,3	13231,4	15208,9	18316,6	28728,3
Tanzania	1520,7	2327,8	2838,5	3319,7	3826,9	4388,1	5054,4	5913,0	7365,4	12312,9
Uzbekistan	2382,6	4074,5	5150,6	6122,7	7099,3	8203,3	9567,8	11410,4	14615,3	26730,2
Vanuatu	944,5	1413,1	1756,4	2119,0	2501,2	2903,4	3361,3	4016,4	5029,4	8860,9
Viet Nam	3818,7	5768,8	7138,2	8432,7	9784,0	11351,7	13317,0	16096,2	20729,5	38173,3
Zambia	546,8	923,1	1260,3	1632,8	2091,3	2669,7	3449,8	4609,0	6636,0	15937,0
Zimbabwe	653,8	883,4	1097,7	1330,1	1604,0	1939,3	2386,5	3043,6	4190,7	8950,1

A.2 The method in a nutshell

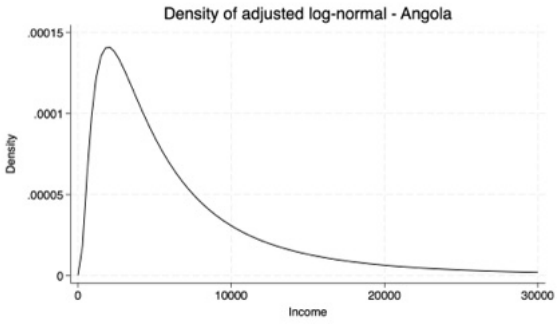
Figure A.1: Methodology pipeline: from grouped data to the missing poor bias

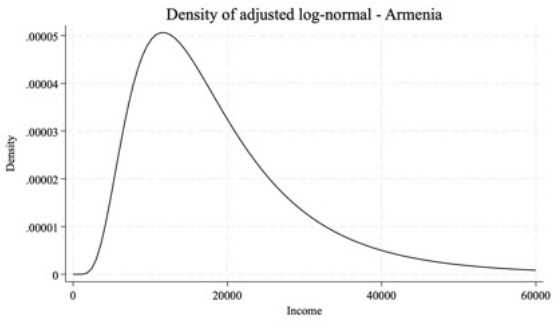


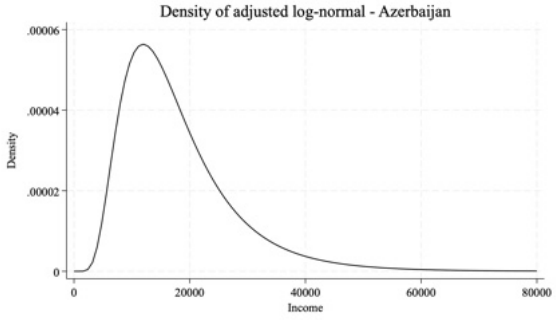
Notes: The pipeline combines two independent data sources (grouped income distributions from PIP/WIID; life expectancy by wealth quintile from the World Bank gradient database) into a country-level estimate of the missing poor bias. Step 1 fits a lognormal distribution to decile means and discretises it into 100 equally spaced income classes. Step 2 estimates a weighted OLS gradient of life expectancy on wealth quintile rank and uses it to impute $\hat{L}_k$ for each income class. Step 3 constructs the adjustment factor $A_k = \hat{L}_{100}/\hat{L}_k$, reweights each class's population, and computes the corrected headcount poverty rate HC^C. The missing poor bias is $HC^C - HC$ expressed in percentage points.

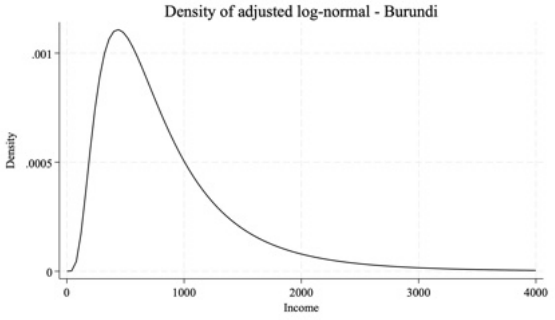
A.3 Income distribution construction

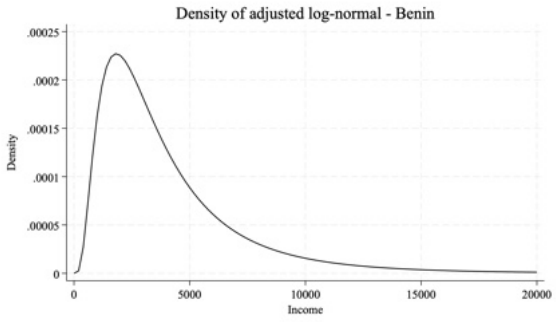
Table A.3: Income distributions

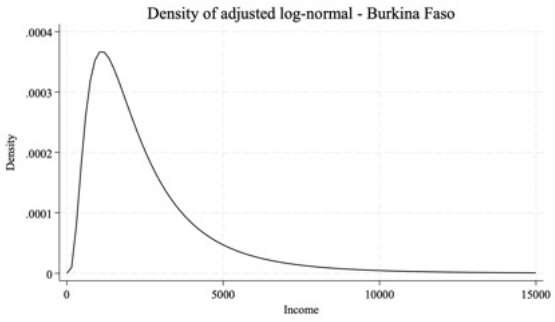


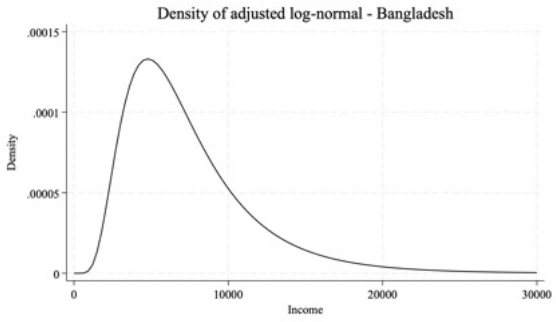












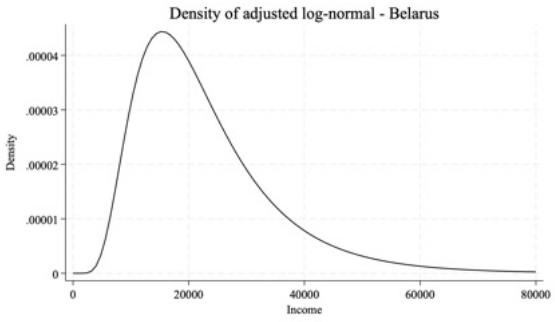
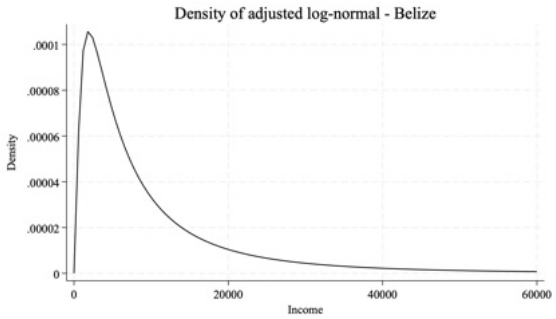
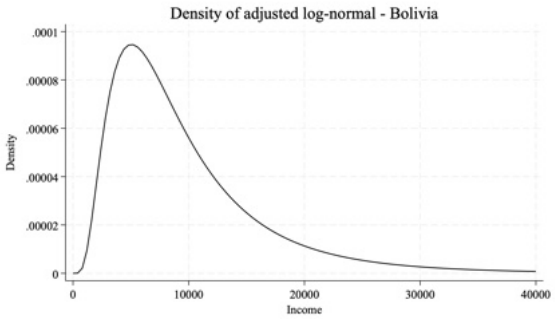
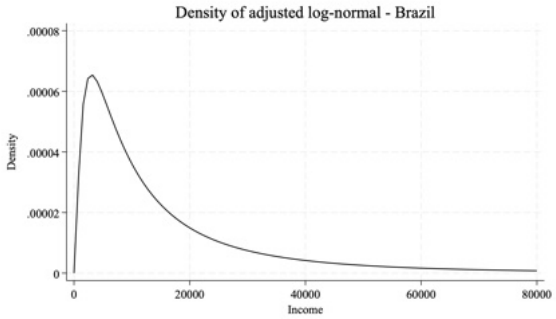
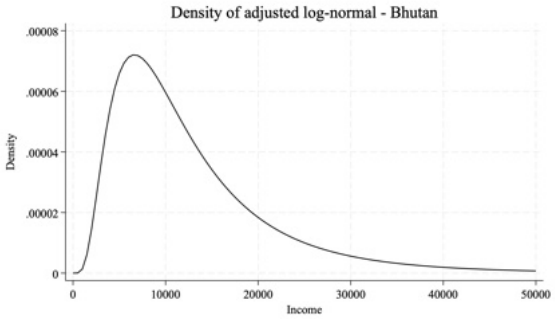


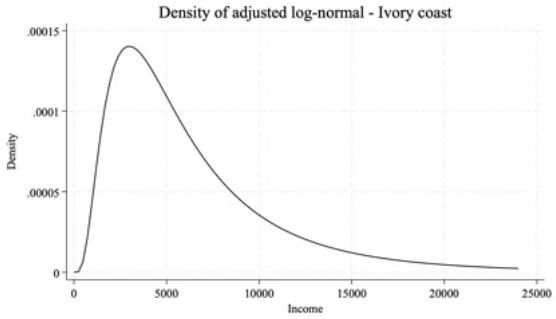
Table A.3: Income distributions

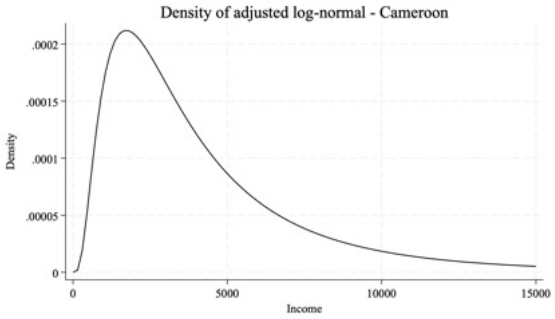


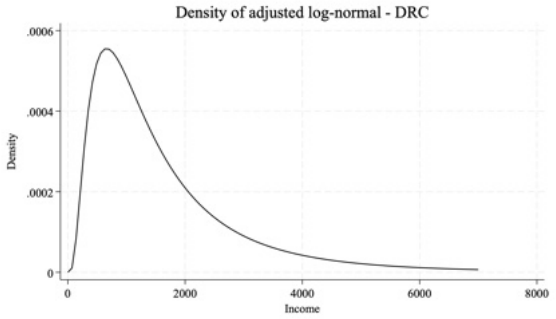


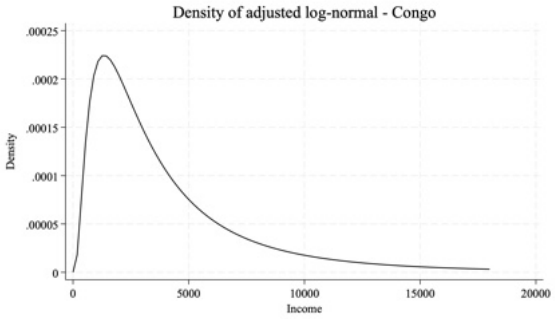


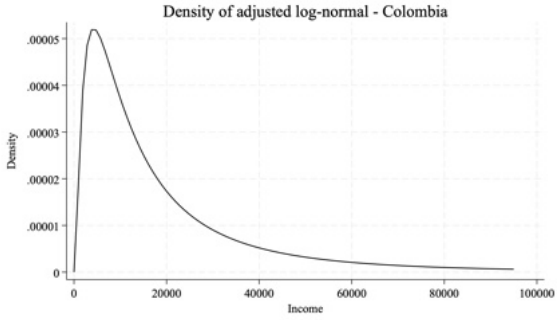












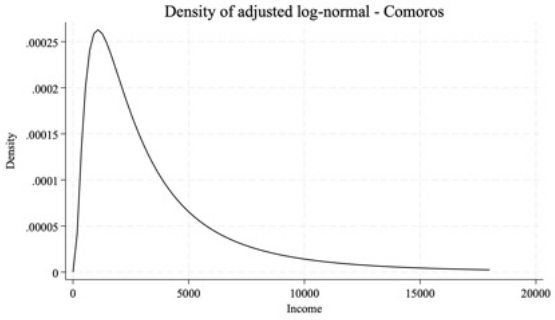
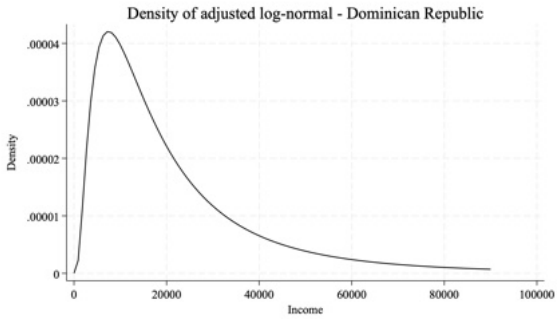
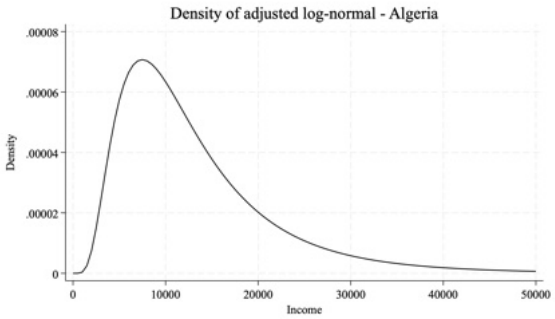
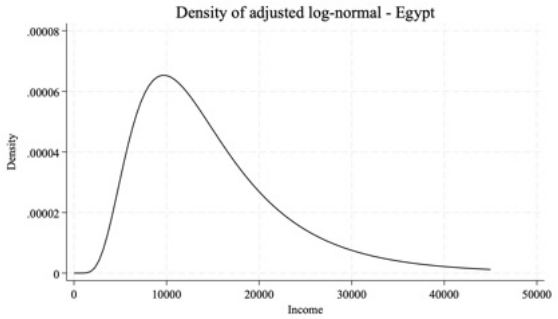
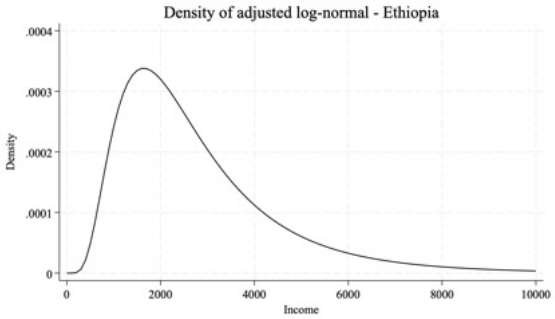


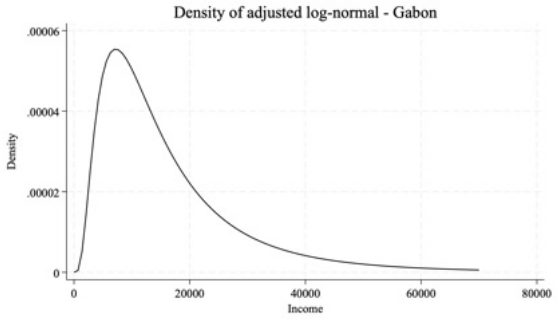
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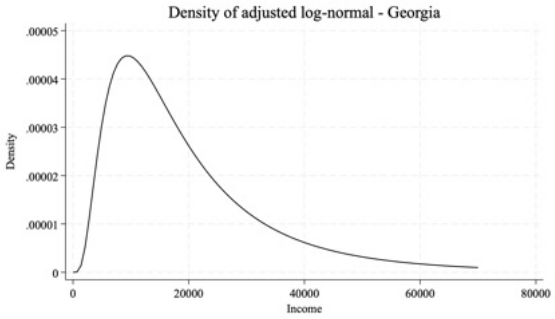


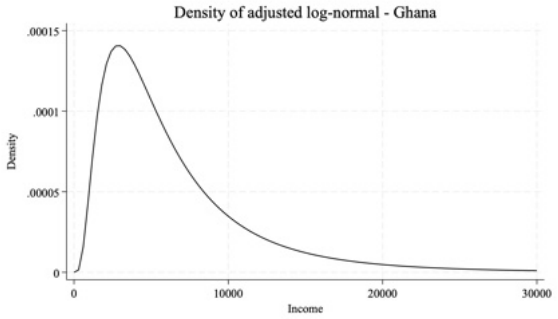


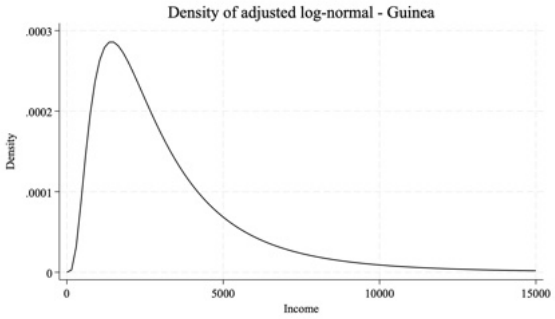


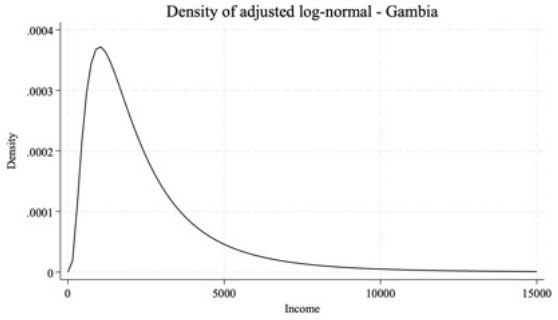












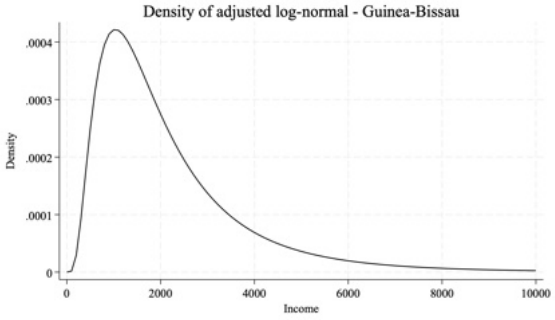
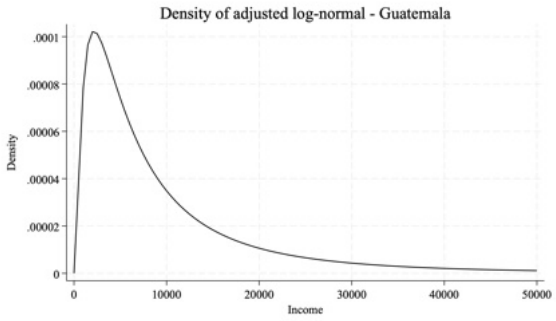
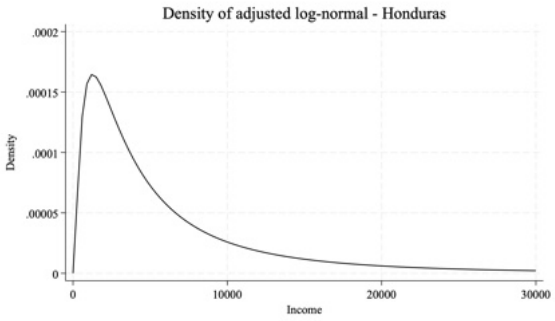
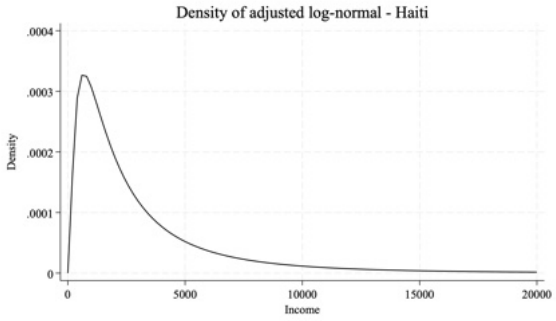
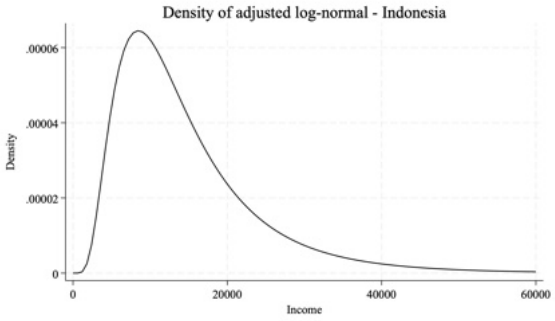


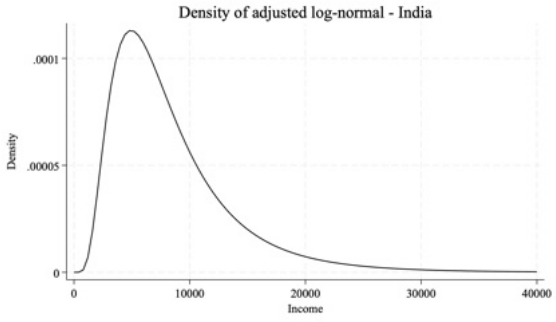
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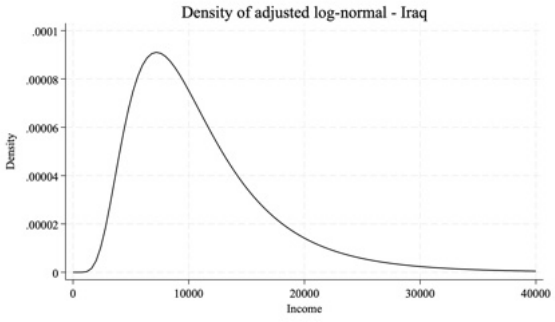


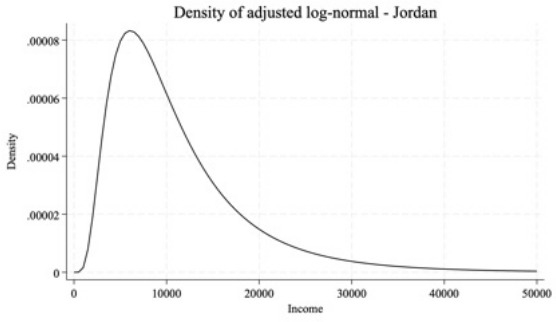


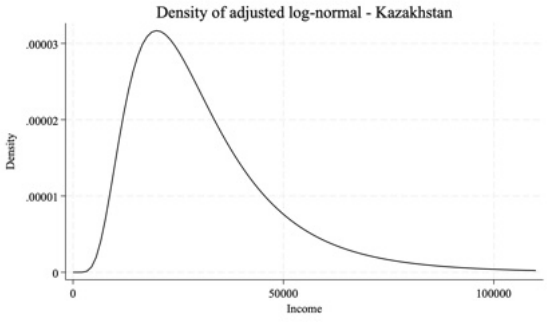


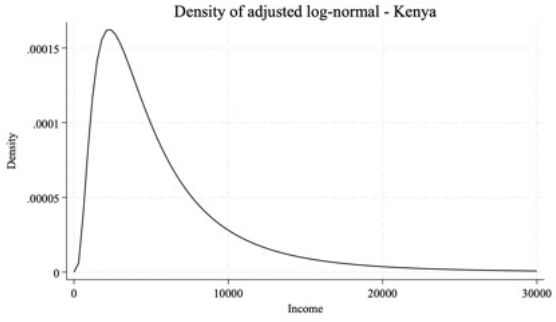












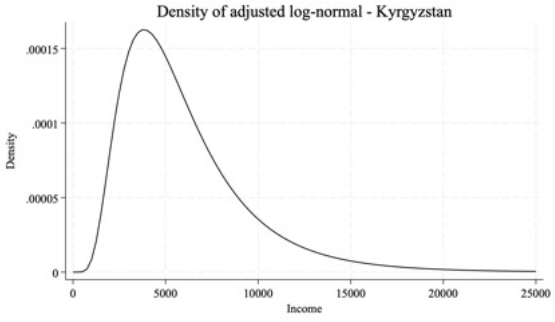
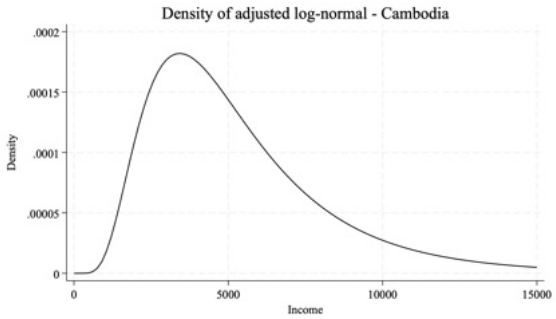
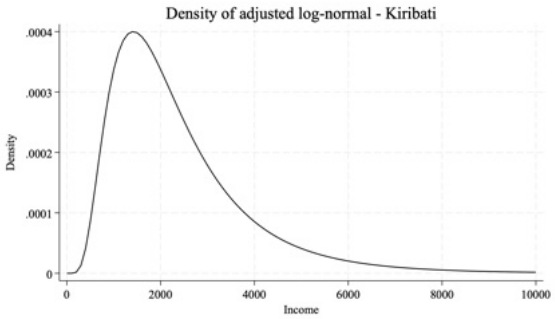
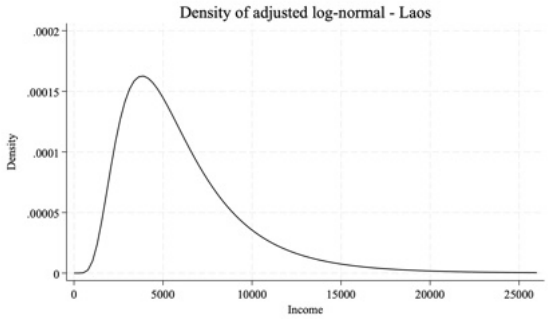
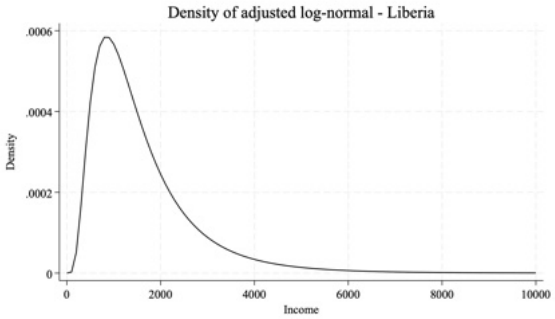


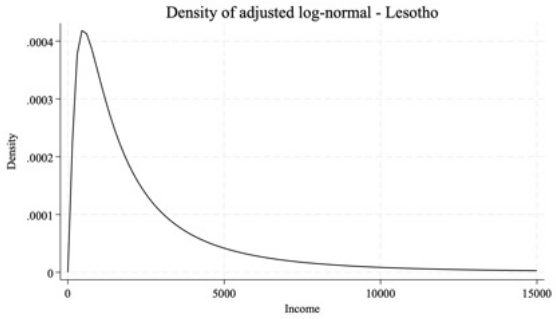
Table A.3: Income distributions

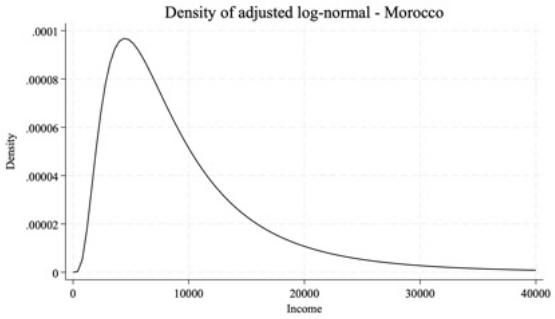


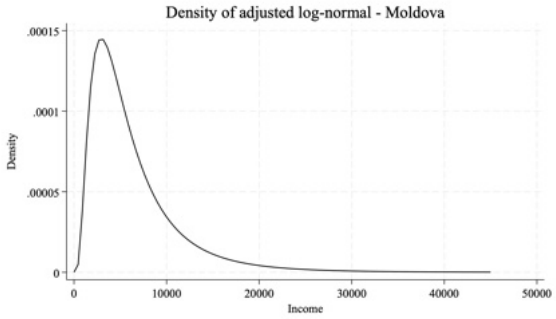


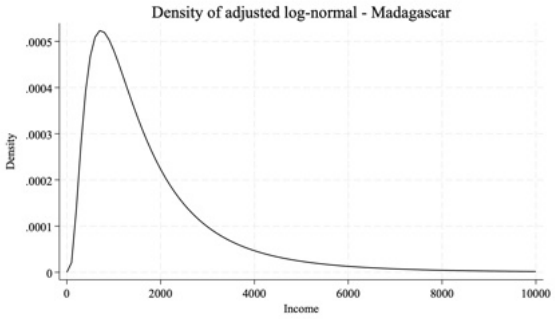


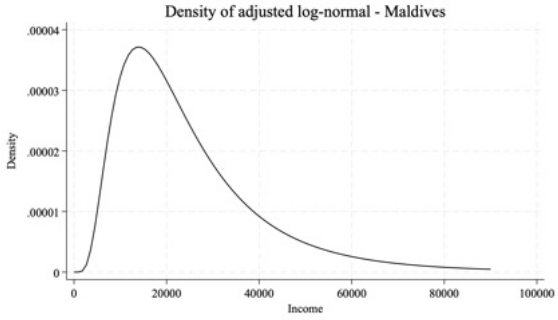












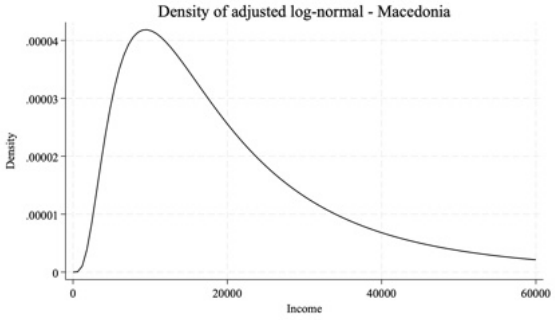
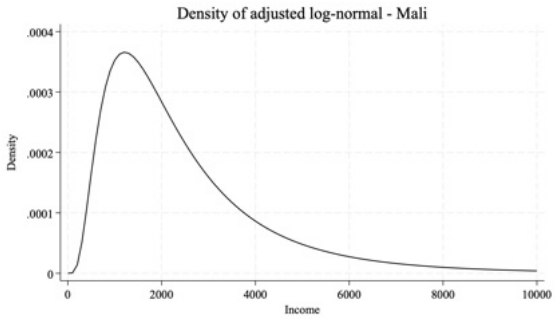
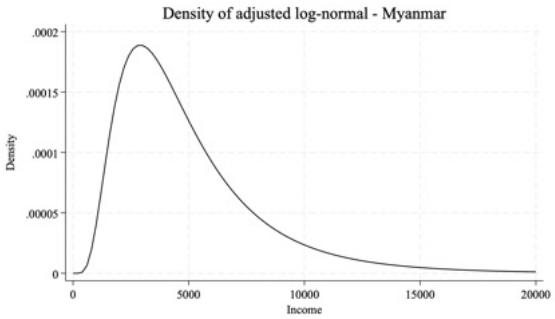
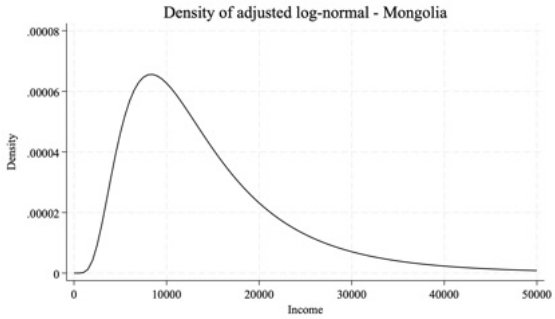
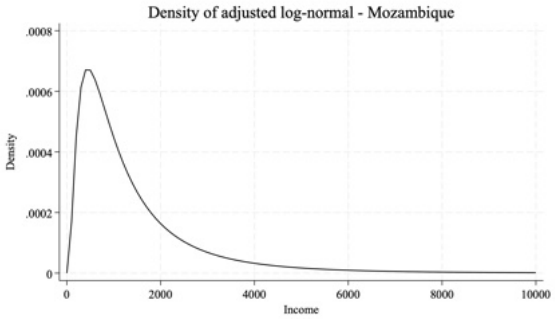


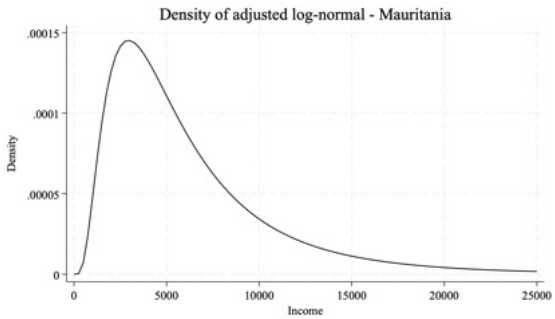
Table A.3: Income distributions

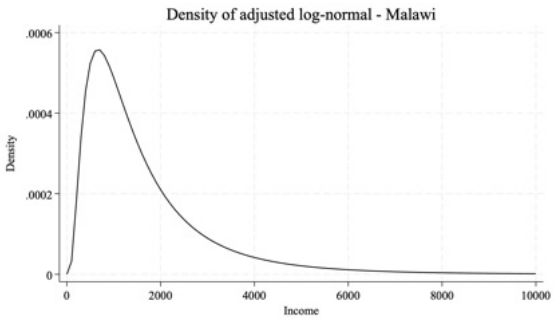


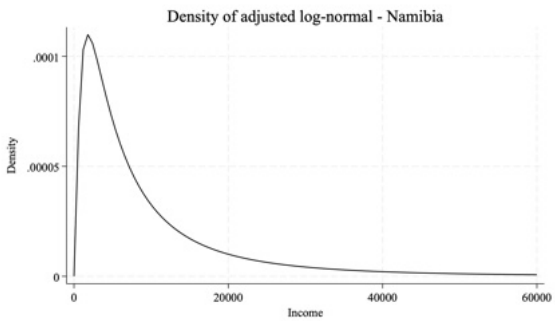


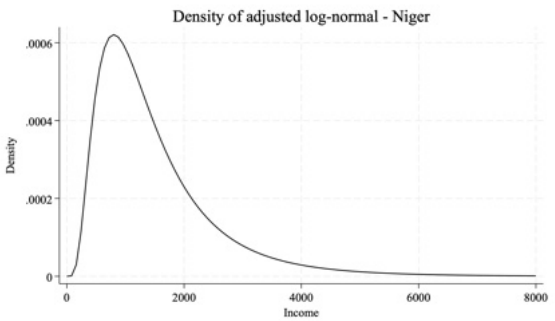


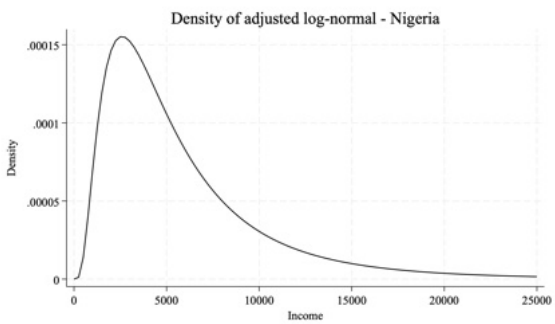












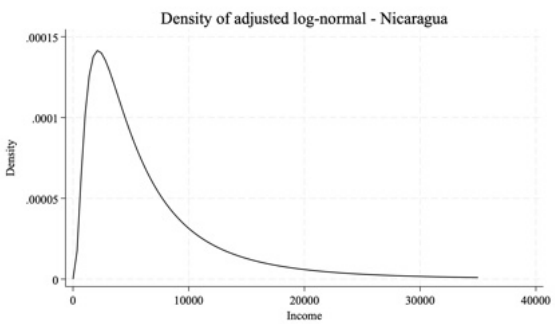
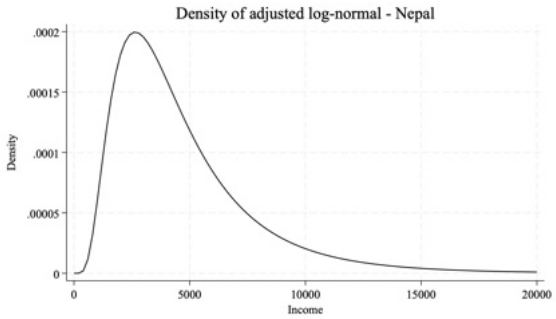
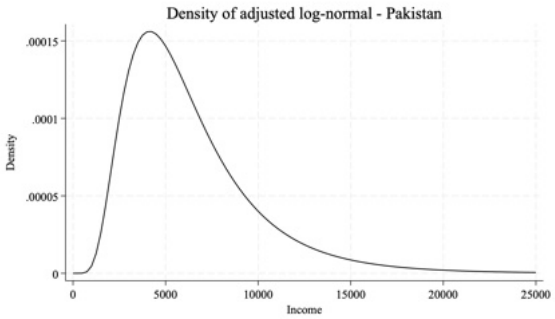
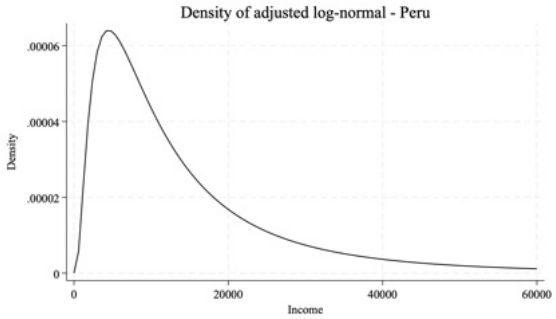
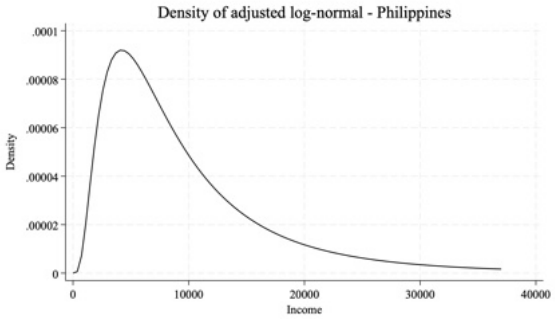


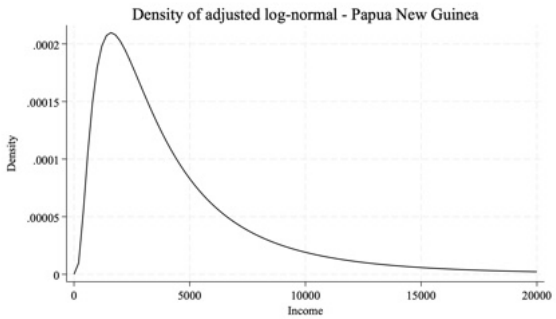
Table A.3: Income distributions

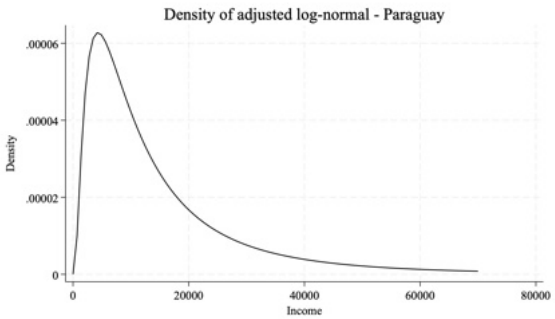


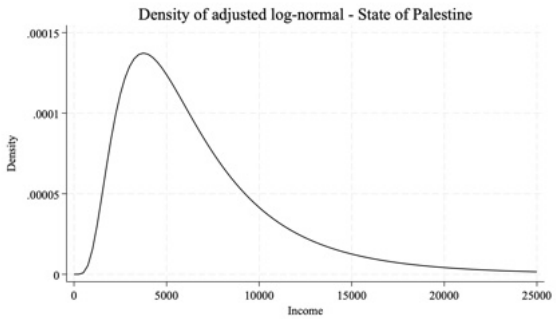


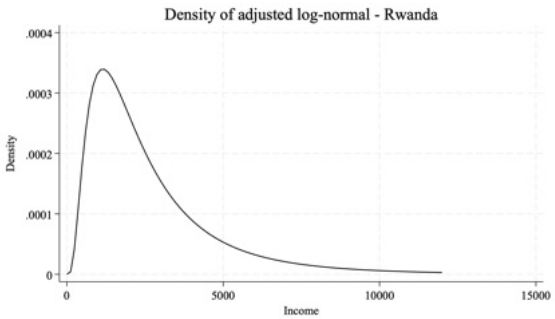


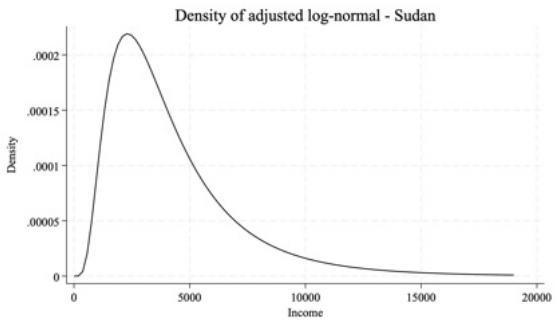












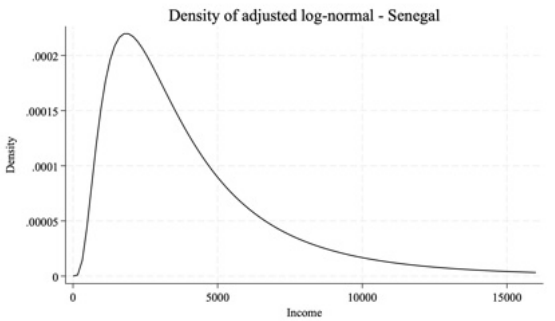
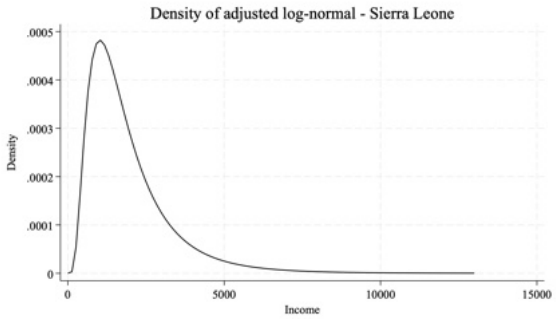
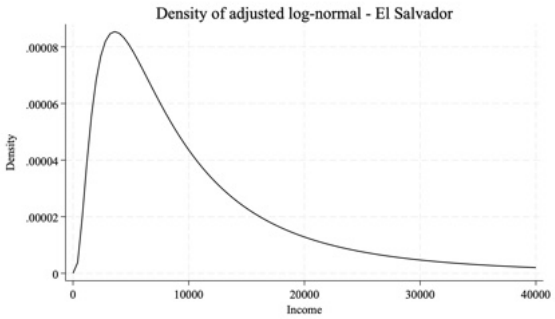
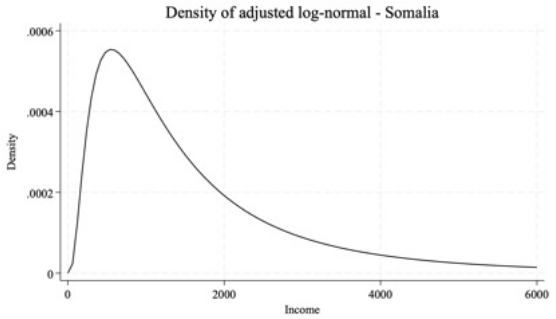
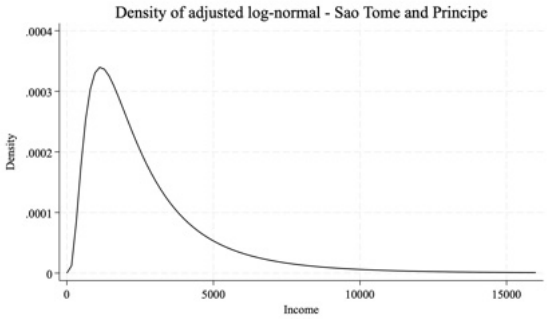


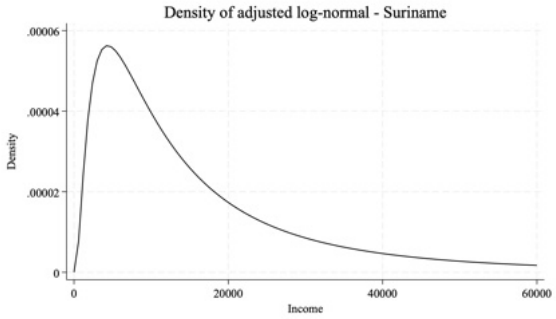
Table A.3: Income distributions

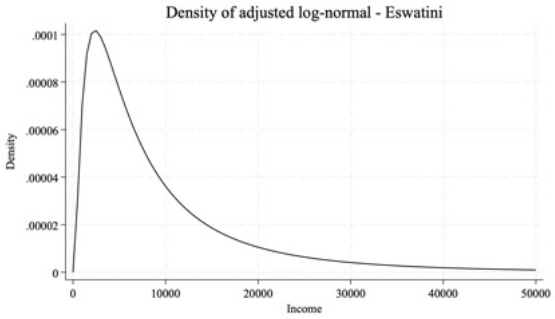


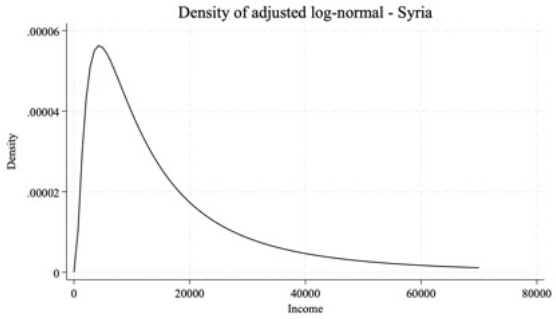


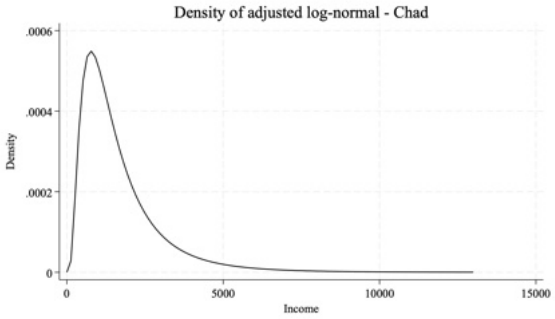


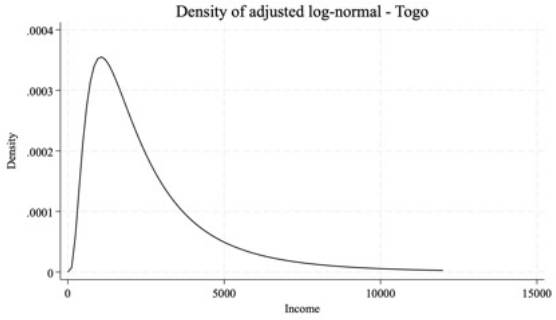












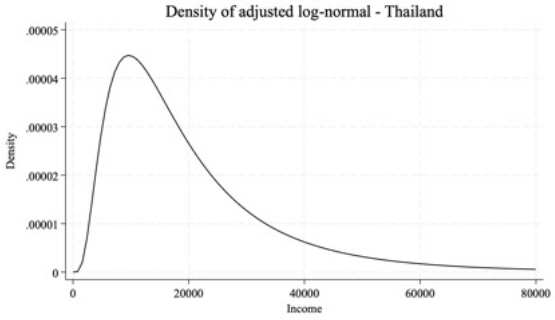
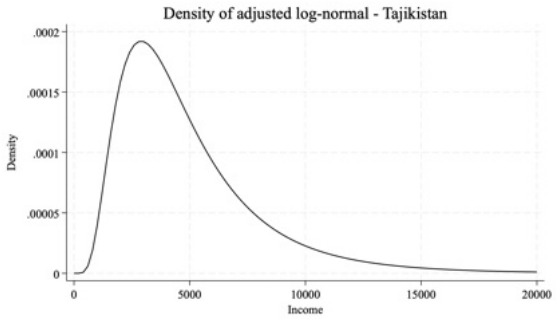
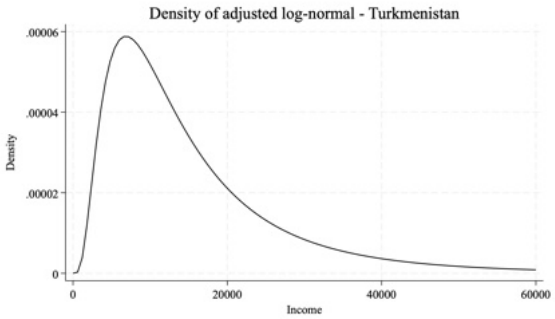
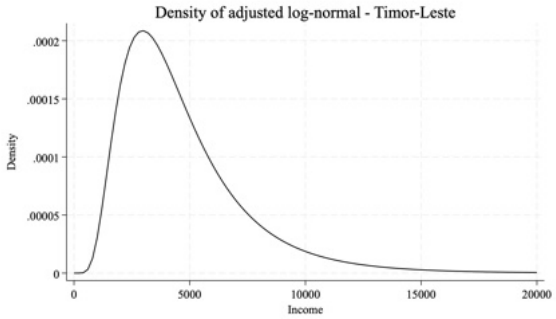
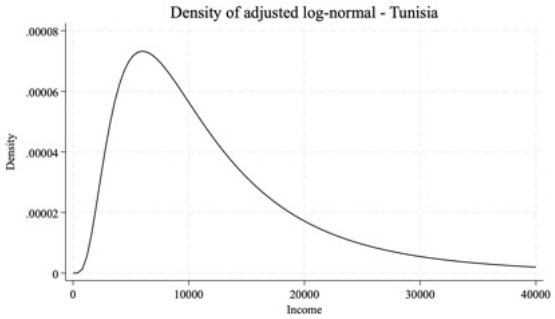


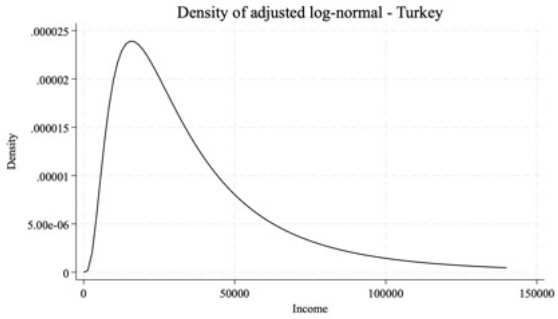
Table A.3: Income distributions

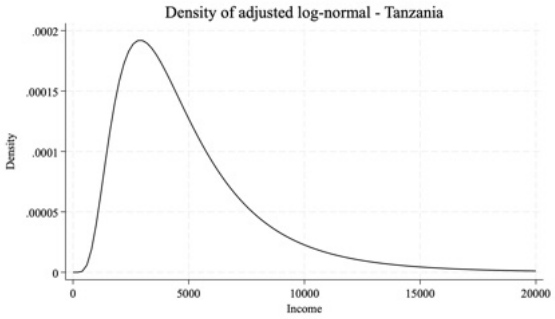


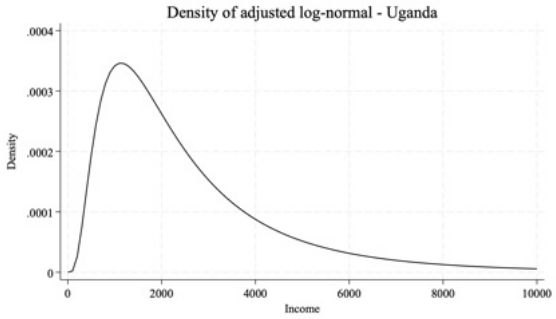


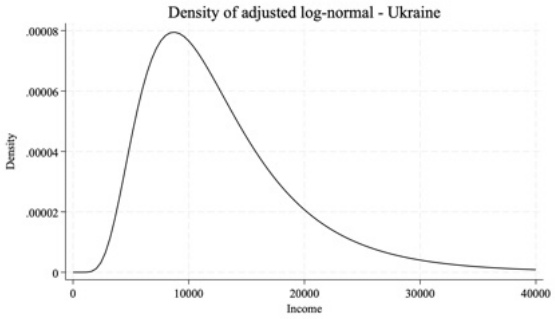


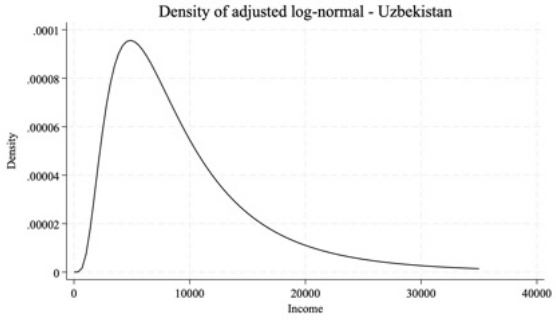












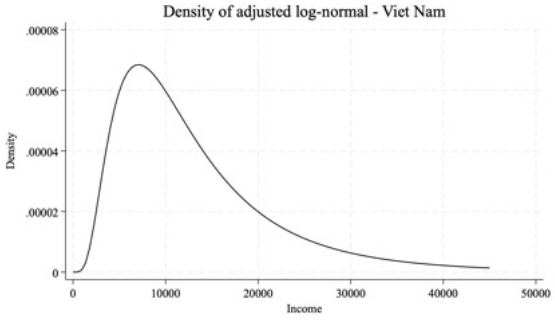
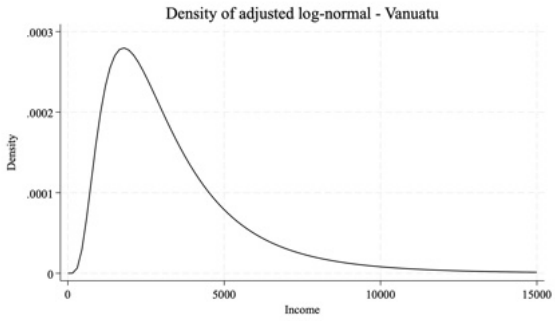
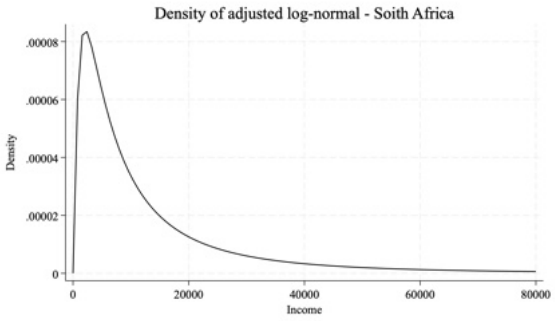
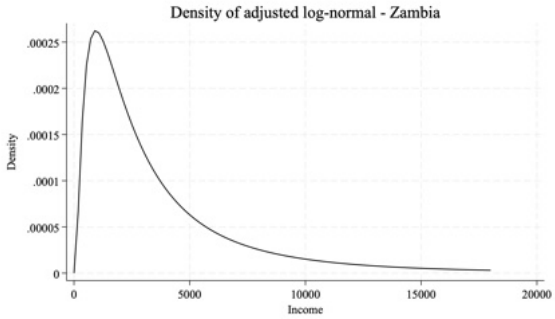
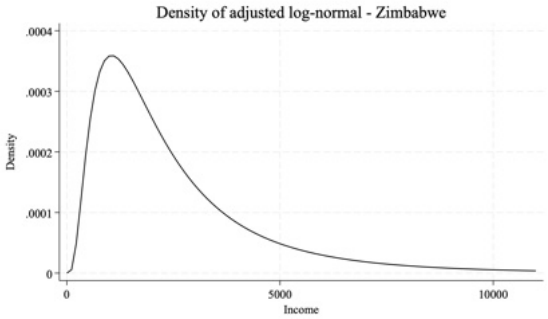


Table A.3: Income distributions









A.4 Regression estimation of the mortality gradient

Table A.4: Mid-point regression of life expectancy by wealth

Country	Constant	Mid-point	R^2
Algeria	72.640	0.028	0.165
Angola	51.253	0.110	0.873
Armenia	74.878	0.016	0.050
Azerbaijan	61.209	0.104	0.586
Bangladesh	59.510	0.092	0.940
Belarus	71.659	0.079	0.285
Belize	70.200	0.150	0.421
Benin	51.484	0.128	0.832
Bhutan	61.720	0.138	0.882
Bolivia	58.887	0.196	0.922
Brazil	67.694	0.185	0.916
Burkina Faso	45.936	0.130	0.790
Burundi	52.636	0.110	0.855
Cambodia	56.277	0.178	0.847
Cameroon	49.501	0.169	0.991
Chad	48.637	0.023	0.089
Colombia	70.308	0.082	0.925
Comoros	61.782	0.068	0.926
Congo	60.348	0.070	0.906
Cote d'Ivoire	50.281	0.128	0.897
DRC	53.939	0.153	0.801
Dominican Republic	65.477	0.105	0.927
Egypt	65.147	0.087	0.916
El Salvador	72.336	0.088	0.365
Eswatini	58.456	0.060	0.533
Ethiopia	56.806	0.033	0.145
Gabon	61.273	0.076	0.834
Gambia	61.752	0.123	0.666
Georgia	64.441	0.169	0.821
Ghana	60.965	0.060	0.837
Guatemala	64.277	0.061	0.879
Guinea	49.181	0.162	0.907
Guinea-Bissau	51.773	0.093	0.868
Guyana	68.263	0.014	0.065
Haiti	56.308	0.083	0.836
Honduras	67.835	0.093	0.946
India	55.125	0.158	0.968
Indonesia	65.460	0.106	0.929
Iraq	70.349	0.037	0.813
Jordan	71.631	0.039	0.972
Kazakhstan	67.389	0.084	0.915
Kenya	58.875	0.090	0.997

Table A.4: Mid-point regression of life expectancy by wealth

Country	Constant	Mid-point	R^2
Kiribati	64.310	0.037	0.327
Kyrgyzstan	69.093	0.063	0.896
Lao	56.720	0.170	0.932
Lesotho	60.727	0.038	0.436
Liberia	56.883	0.022	0.533
Macedonia	76.159	0.103	0.287
Madagascar	55.667	0.130	0.792
Malawi	53.674	0.085	0.674
Maldives	76.556	0.005	0.003
Mali	43.652	0.180	0.751
Mauritania	60.381	0.104	0.966
Moldova	78.486	0.024	0.035
Mongolia	63.685	0.114	0.954
Morocco	64.327	0.173	0.958
Mozambique	51.843	0.079	0.832
Myanmar	61.430	0.125	0.848
Namibia	67.191	0.095	0.703
Nepal	60.992	0.087	0.896
Nicaragua	63.649	0.113	0.875
Niger	39.092	0.128	0.461
Nigeria	43.434	0.227	0.931
Pakistan	55.693	0.114	0.938
Papua New Guinea	66.373	0.058	0.957
Paraguay	62.483	0.203	0.728
Peru	70.911	0.151	0.985
Philippines	64.358	0.127	0.960
Rwanda	54.736	0.074	0.710
Sao Tome and P.	65.172	0.026	0.308
Senegal	58.780	0.139	0.957
Sierra Leone	50.144	0.081	0.410
Somalia	54.829	0.036	0.338
South Africa	58.701	0.185	0.952
State of Palestine	70.132	0.089	0.741
Sudan	63.992	0.078	0.834
Suriname	75.666	0.018	0.399
Syria	73.846	0.045	0.830
Tajikistan	64.512	0.049	0.632
Tanzania	58.766	0.033	0.935
Thailand	82.166	0.122	0.786
Timor-Leste	64.486	0.067	0.851
Togo	50.851	0.195	0.949
Tunisia	77.656	0.001	0.000
Turkey	62.860	0.141	0.975
Turkmenistan	68.024	0.080	0.946

Table A.4: Mid-point regression of life expectancy by wealth

Country	Constant	Mid-point	R^2
Uganda	56.667	0.085	0.811
Ukraine	71.854	0.161	0.915
Uzbekistan	67.179	0.022	0.454
Vanuatu	64.099	0.113	0.450
Viet Nam	69.526	0.154	0.991
Zambia	54.929	0.065	0.668
Zimbabwe	61.508	0.056	0.803

A.5 Life expectancy by income

Table A.5: Life expectancy by income class

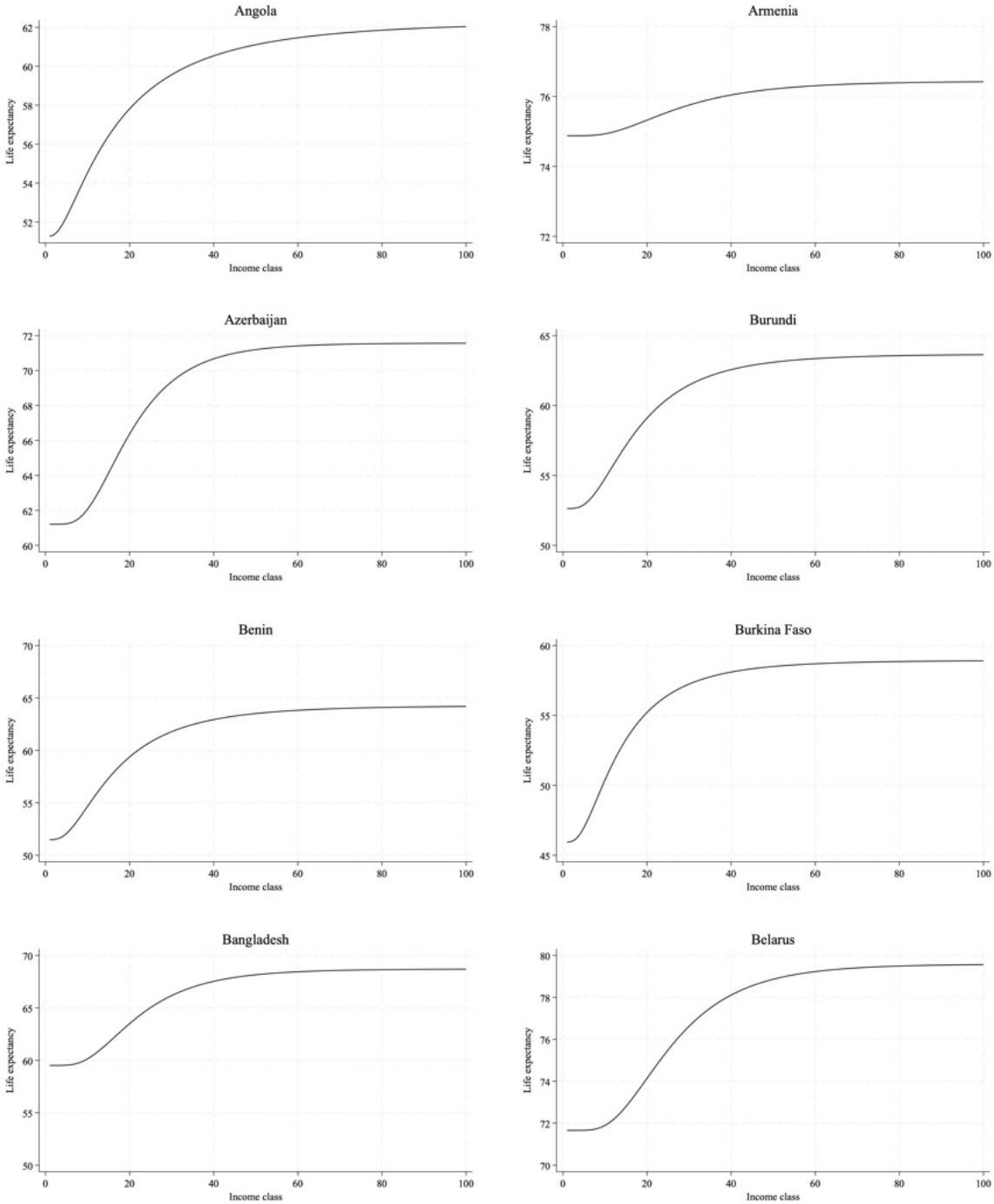
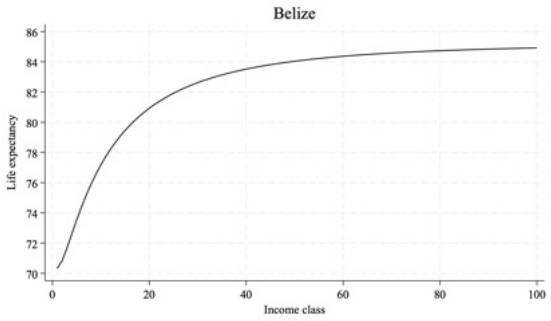
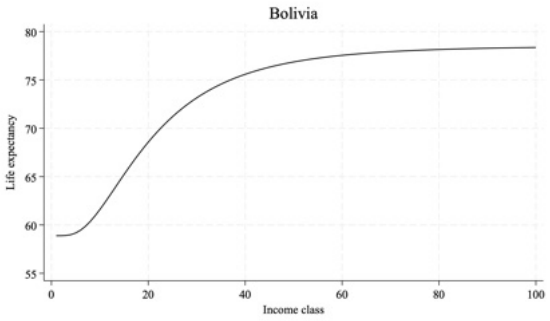
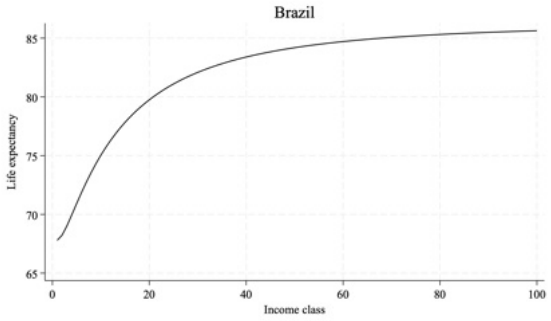
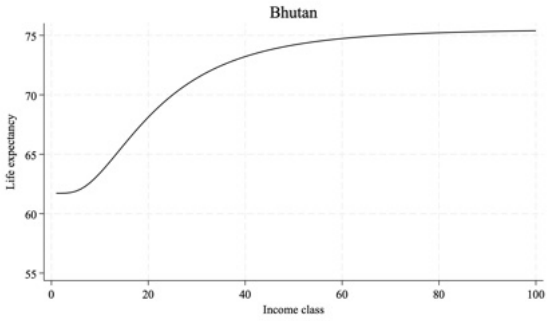


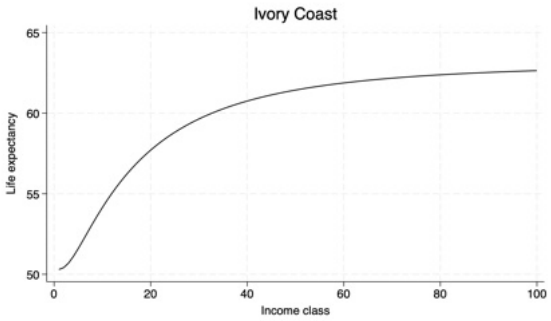
Table A.5: Life expectancy by income class

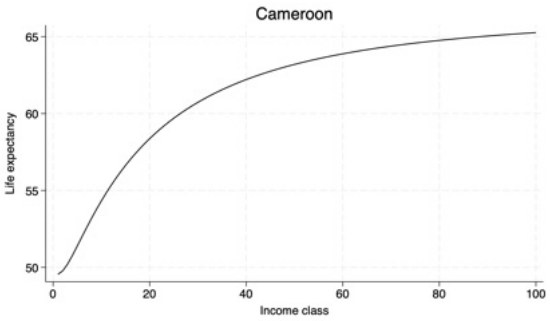


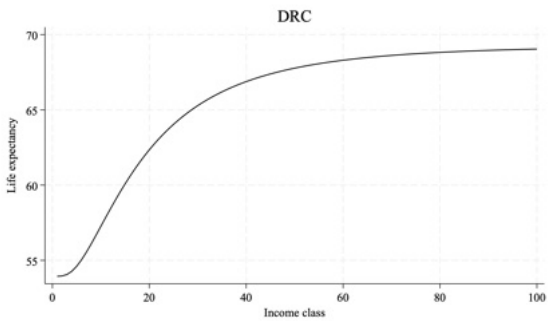


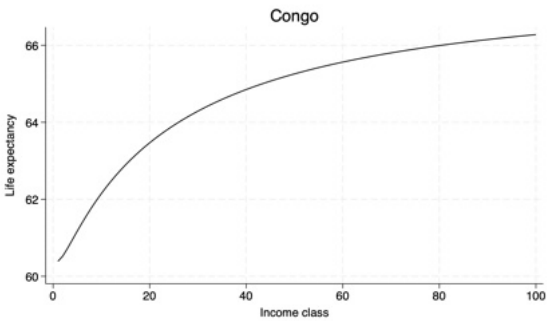


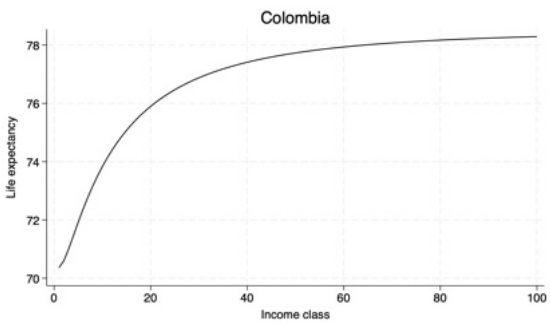












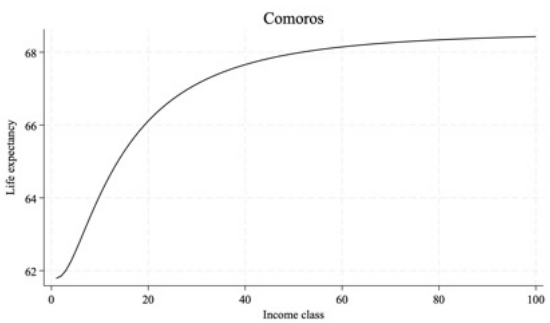


Table A.5: Life expectancy by income class

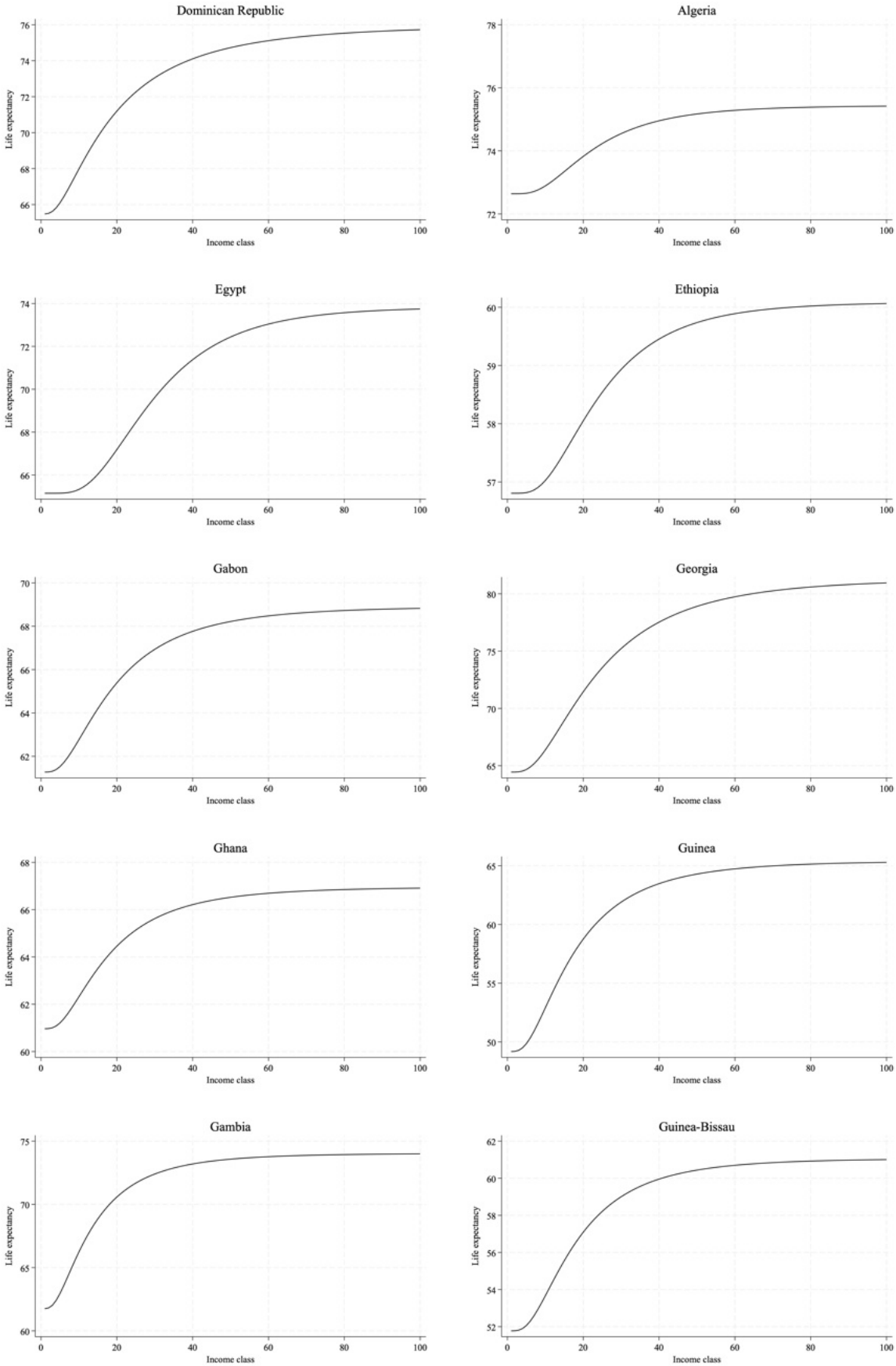


Table A.5: Life expectancy by income class

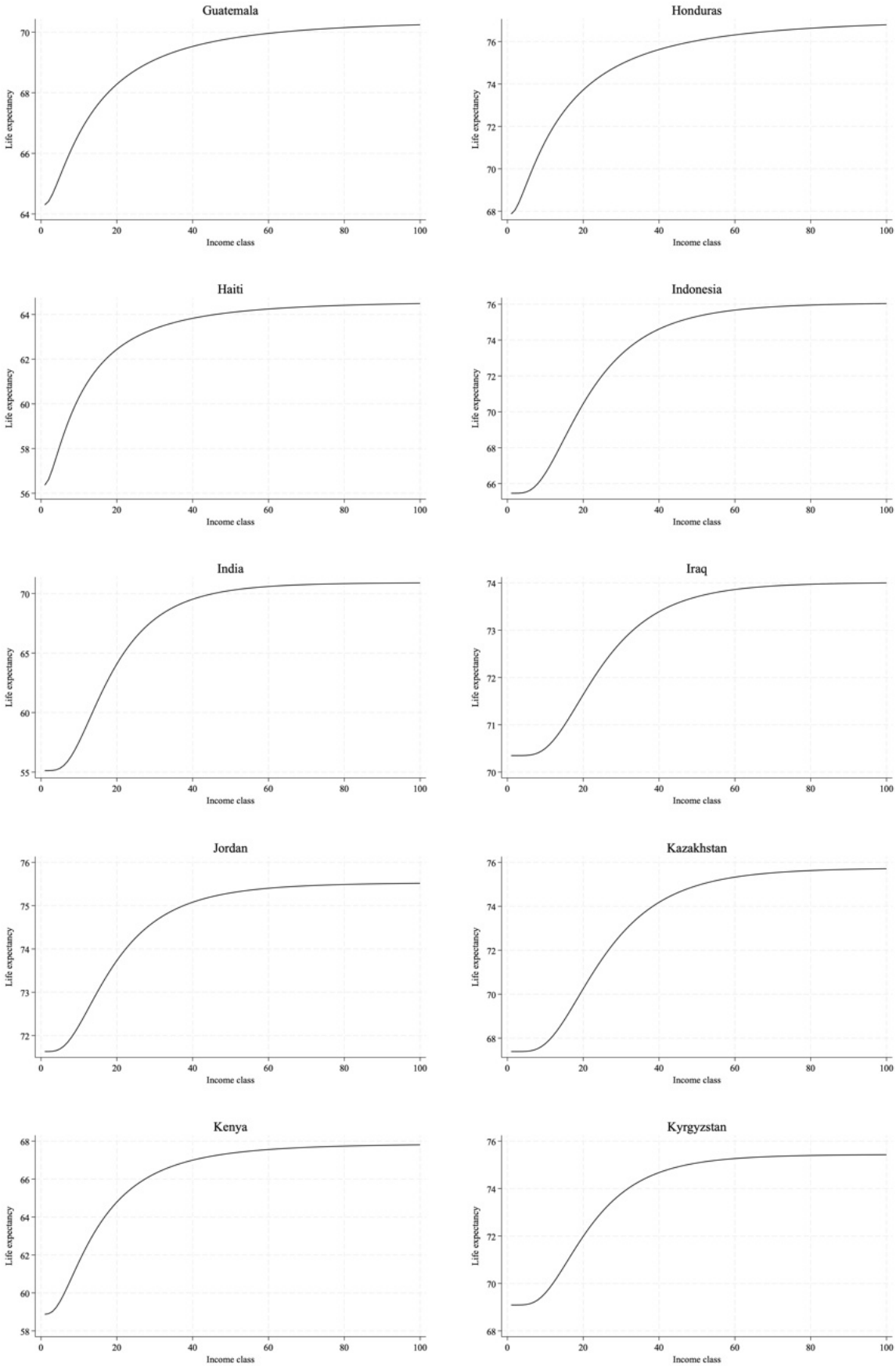


Table A.5: Life expectancy by income class

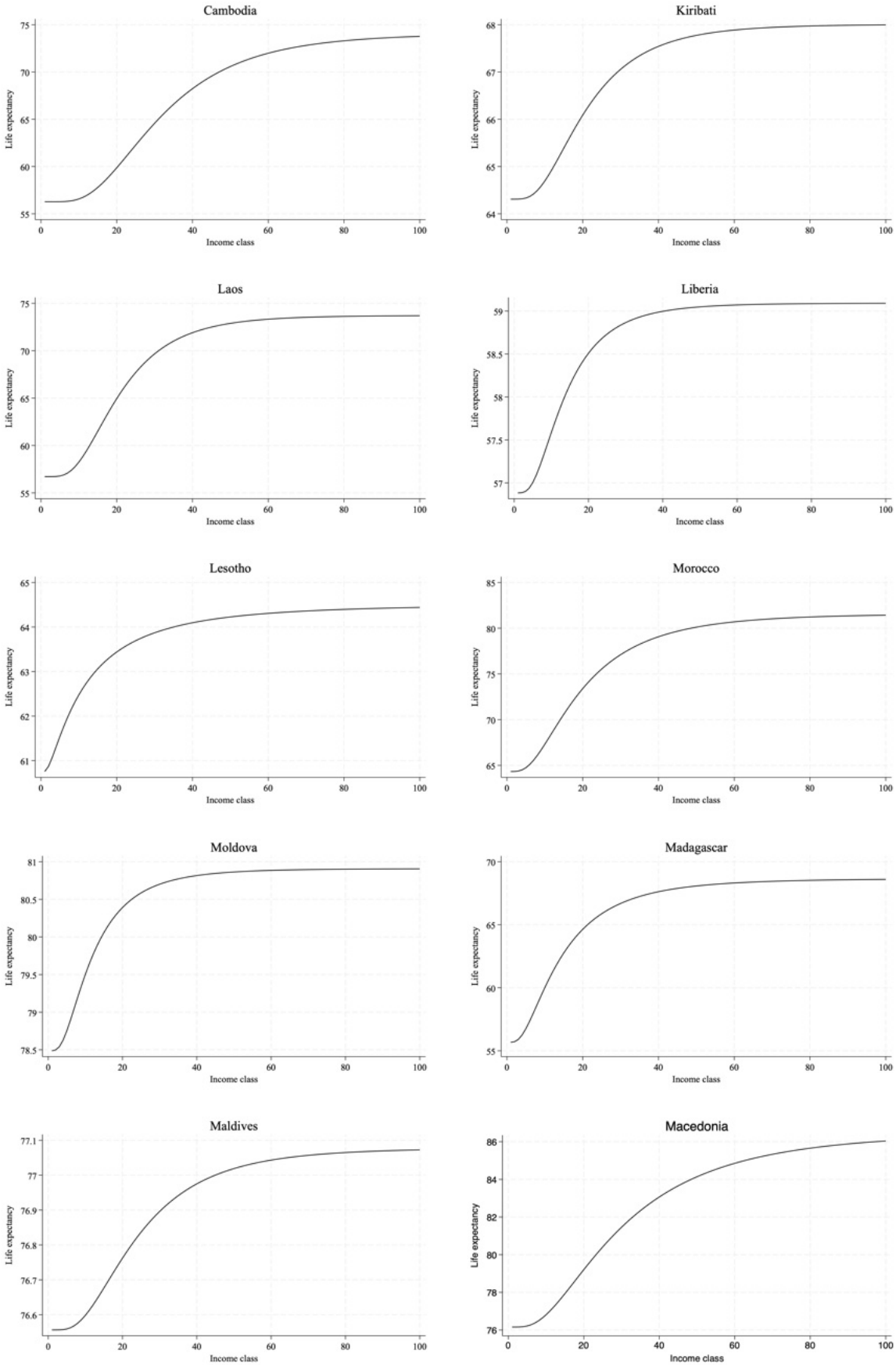
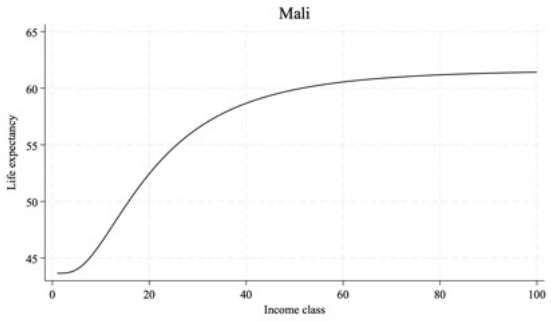
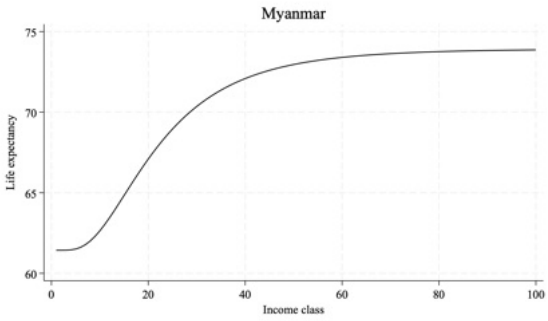
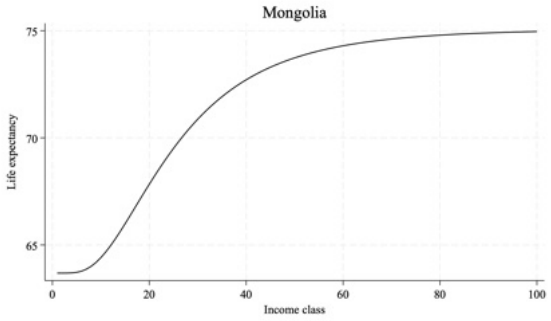
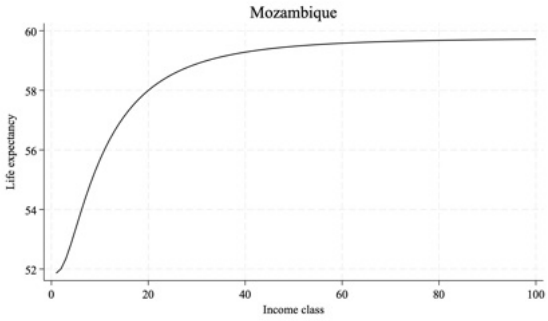


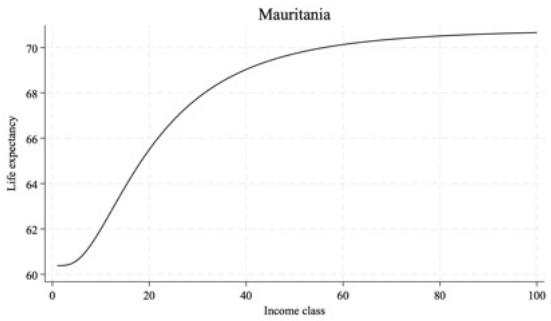
Table A.5: Life expectancy by income class

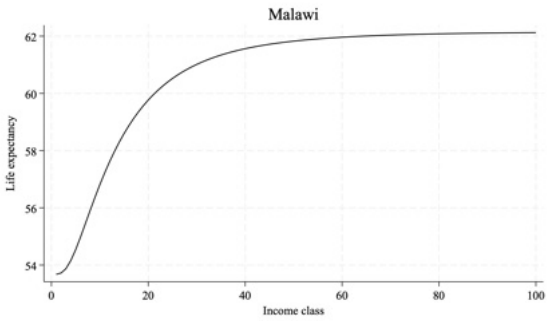


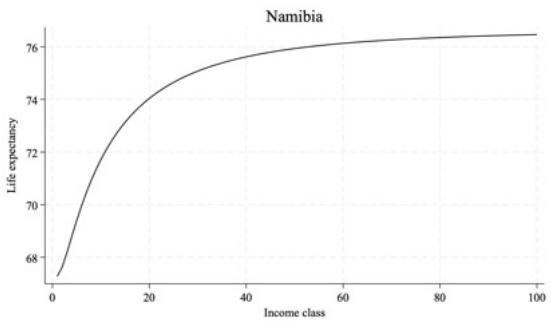


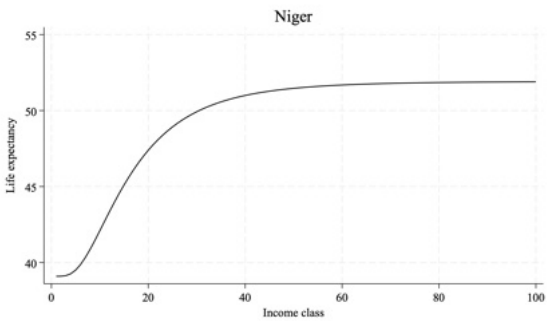


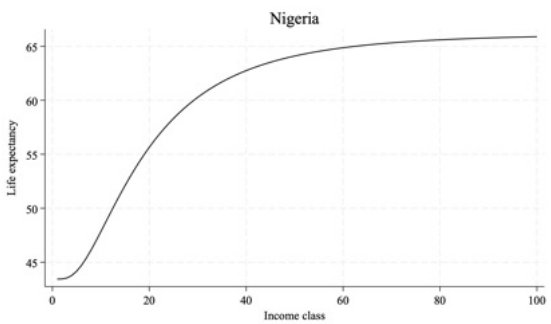












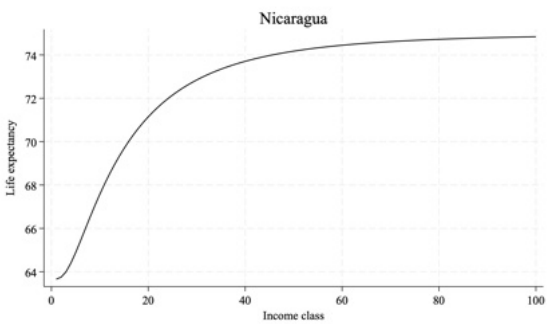


Table A.5: Life expectancy by income class

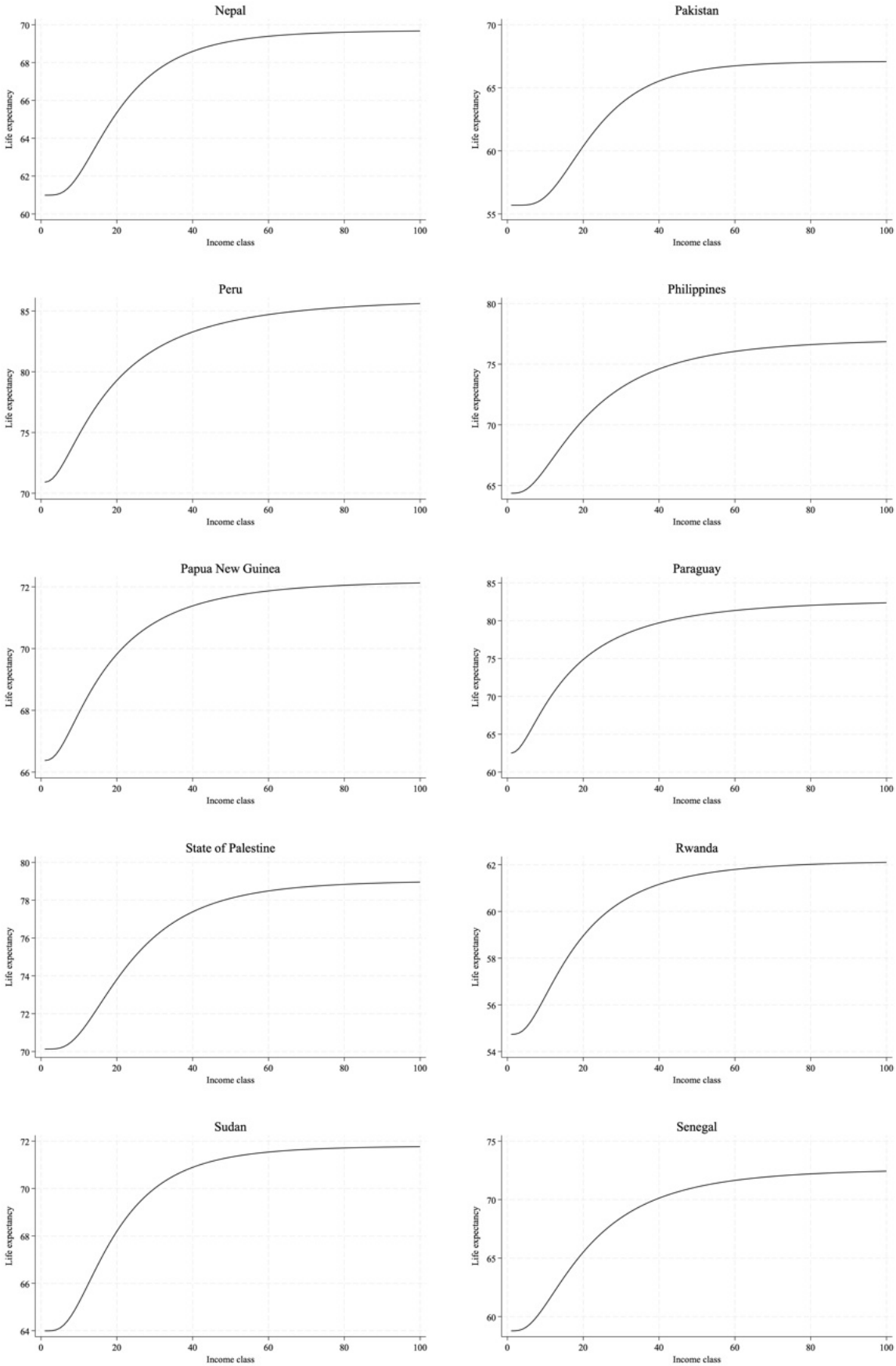
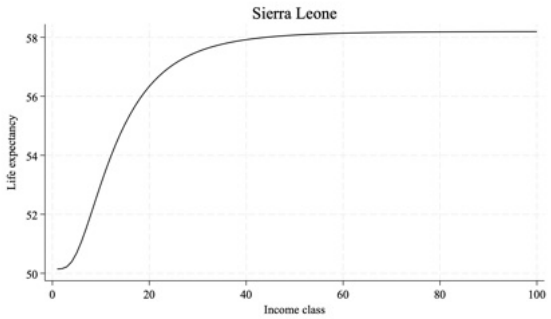
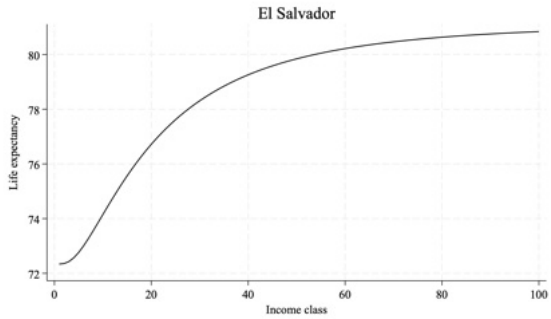
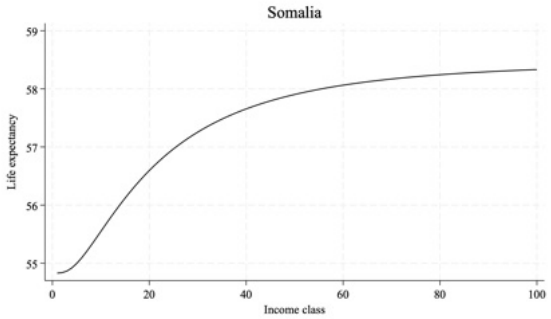
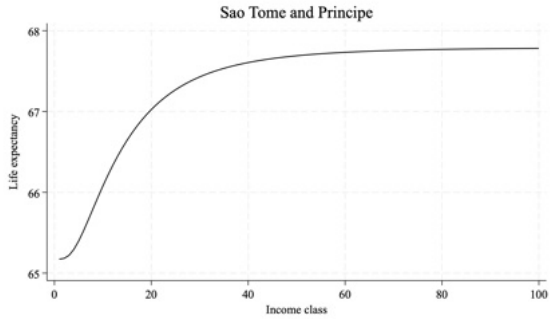


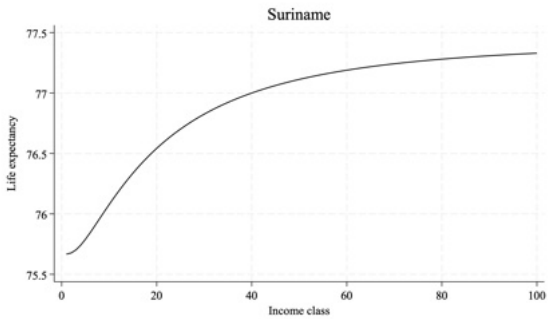
Table A.5: Life expectancy by income class

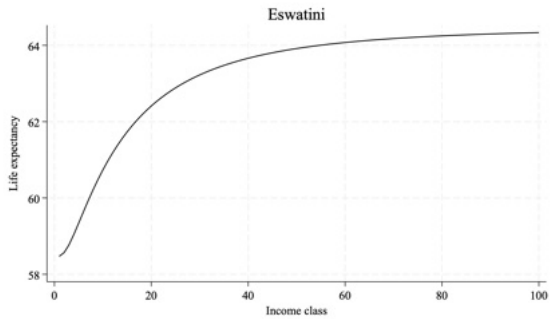


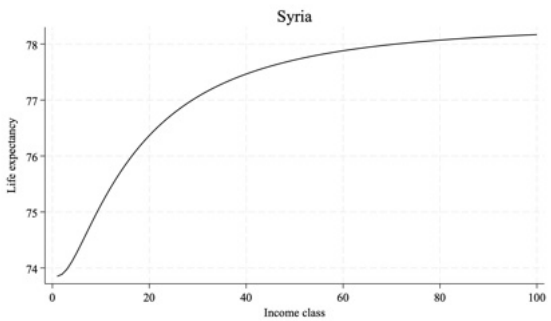


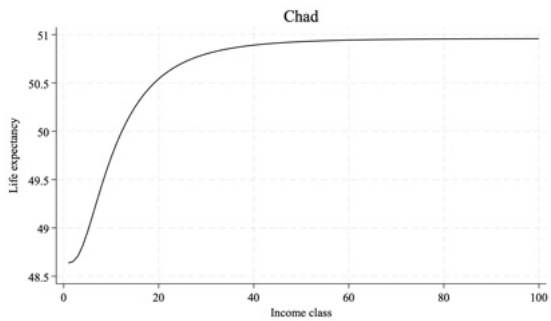


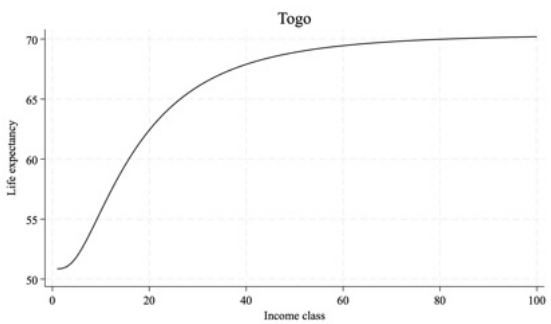












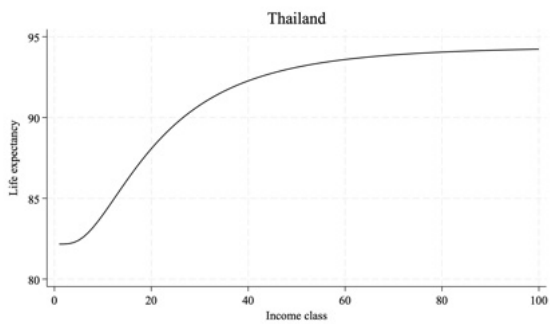


Table A.5: Life expectancy by income class

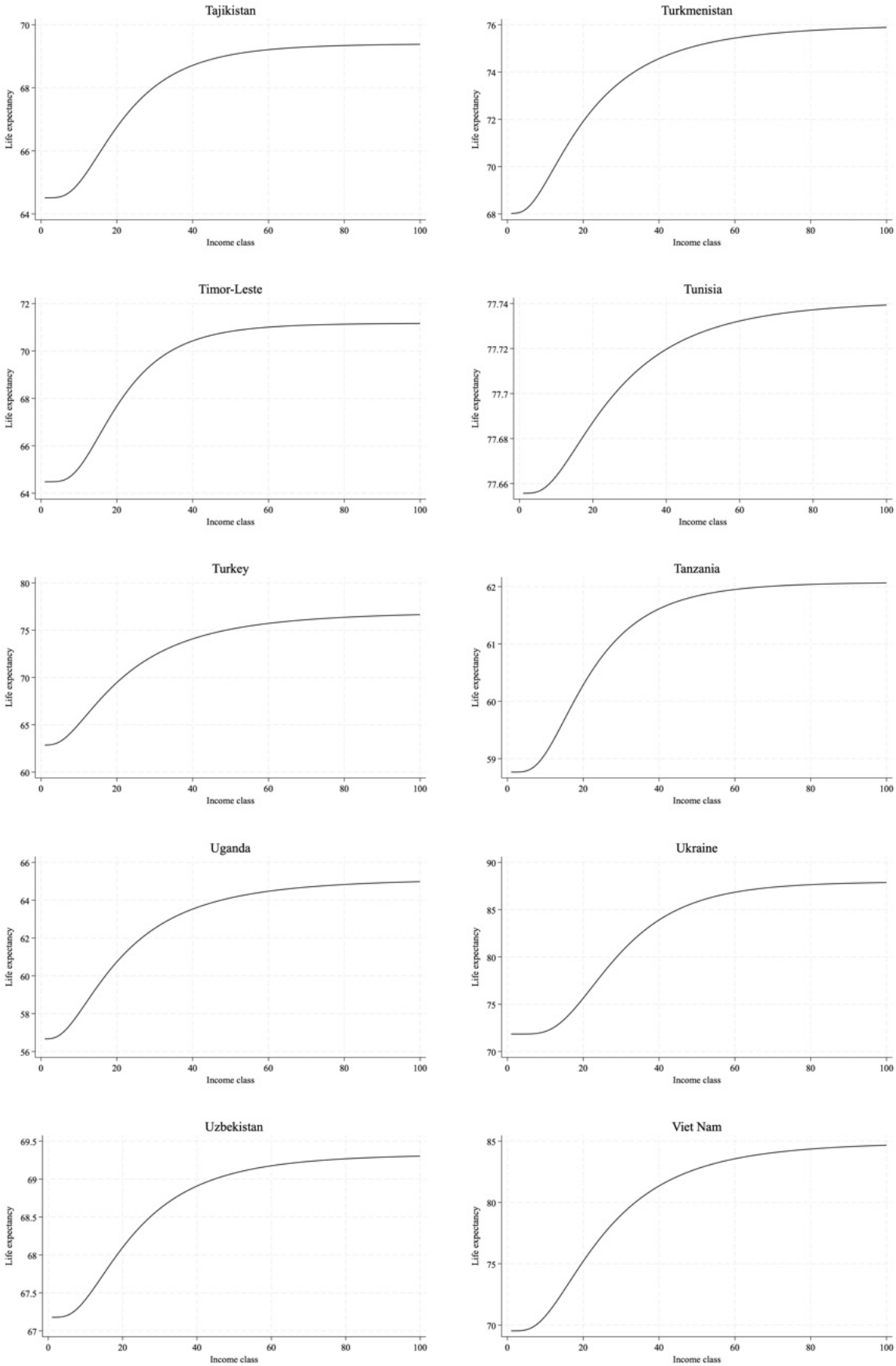


Table A.5: Life expectancy by income class

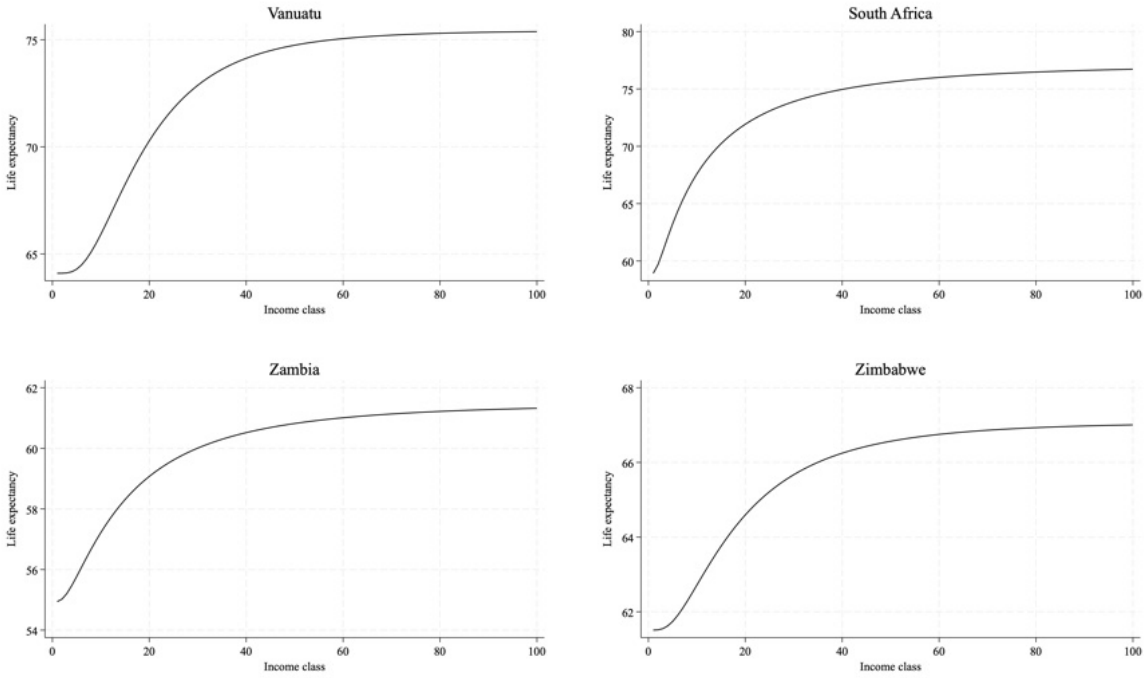


Table A.6: Adjustment factors for the bottom class

	Life expectancy		Adjustment factor
	Bottom income class	Top income class	
Algeria	72.64	75.42	1.04
Angola	51.26	62.04	1.21
Armenia	74.88	76.42	1.02
Azerbaijan	61.21	71.56	1.17
Bangladesh	59.51	68.69	1.15
Belarus	71.66	79.56	1.11
Belize	70.32	84.92	1.21
Benin	51.48	64.19	1.25
Bhutan	61.72	75.39	1.22
Bolivia	58.89	78.36	1.33
Brazil	67.79	85.63	1.26
Burkina Faso	45.94	58.91	1.28
Burundi	52.64	63.63	1.21
Cambodia	56.28	73.77	1.31
Cameroon	49.50	65.96	1.33
Chad	48.64	50.96	1.05
Colombia	70.34	78.28	1.11
Comoros	61.79	68.43	1.11
Congo	60.35	67.18	1.11
Cote d'Ivoire	50.28	62.84	1.25
DRC	53.94	69.04	1.28
Dominican Republic	65.48	75.72	1.16
Egypt	65.15	73.74	1.13
El Salvador	72.34	80.84	1.12
Eswatini	58.47	64.33	1.10
Ethiopia	56.81	60.06	1.06
Gabon	61.27	68.83	1.12
Gambia	61.76	73.99	1.20
Georgia	64.44	80.96	1.26
Ghana	60.96	66.91	1.10
Guatemala	64.30	70.24	1.09
Guinea	49.18	65.28	1.33
Guinea-Bissau	51.77	61.00	1.18
Haiti	56.36	64.49	1.14
Honduras	67.87	76.80	1.13
India	55.13	70.89	1.29
Indonesia	65.46	76.04	1.16
Iraq	70.35	74.00	1.05
Jordan	71.63	75.52	1.05
Kazakhstan	67.39	75.71	1.12
Kenya	58.88	67.81	1.15
Kiribati	64.31	68.00	1.06
Kyrgyzstan	69.09	75.43	1.09

Table A.6: Adjustment factors for the bottom class

	Life expectancy		Adjustment factor
	Bottom income class	Top income class	
Lao	56.72	73.69	1.30
Lesotho	60.75	64.44	1.06
Liberia	56.88	59.09	1.04
Macedonia	76.16	86.00	1.13
Madagascar	55.67	68.60	1.23
Malawi	53.68	62.12	1.16
Maldives	76.56	77.07	1.01
Mali	43.65	61.42	1.41
Mauritania	60.38	70.66	1.17
Moldova	78.49	80.91	1.03
Mongolia	63.68	74.96	1.18
Morocco	64.33	81.42	1.27
Mozambique	51.86	59.72	1.15
Myanmar	61.43	73.87	1.20
Namibia	67.28	76.46	1.14
Nepal	60.99	69.67	1.14
Nicaragua	63.66	74.84	1.18
Niger	39.09	51.89	1.33
Nigeria	43.43	65.88	1.52
Pakistan	55.69	67.08	1.20
Papua New Guinea	66.37	72.13	1.09
Paraguay	62.50	82.37	1.32
Peru	70.92	85.62	1.21
Philippines	64.36	76.85	1.19
Rwanda	54.74	62.10	1.13
Sao Tome and P.	65.17	67.78	1.04
Senegal	58.78	72.43	1.23
Sierra Leone	50.14	58.19	1.16
Somalia	54.83	58.33	1.06
South Africa	58.92	76.72	1.30
State of Palestine	70.13	78.96	1.13
Sudan	63.99	71.77	1.12
Suriname	75.67	77.33	1.02
Syria	73.85	78.17	1.06
Tajikistan	64.51	69.38	1.08
Tanzania	58.77	62.07	1.06
Thailand	82.17	94.23	1.15
Timor-Leste	64.49	71.16	1.10
Togo	50.85	70.19	1.38
Tunisia	77.66	77.74	1.00
Turkey	62.86	76.64	1.22
Turkmenistan	68.02	75.89	1.12
Uganda	56.67	64.98	1.15

Table A.6: Adjustment factors for the bottom class

	Life expectancy		Adjustment factor
	Bottom income class	Top income class	
Ukraine	71.85	87.87	1.22
Uzbekistan	67.18	69.30	1.03
Vanuatu	64.10	75.38	1.18
Viet Nam	69.53	84.67	1.22
Zambia	54.94	61.32	1.12
Zimbabwe	61.51	67.01	1.09

A.6 Corrected distributions of income

Table A.7: Distribution of income class before and after correction

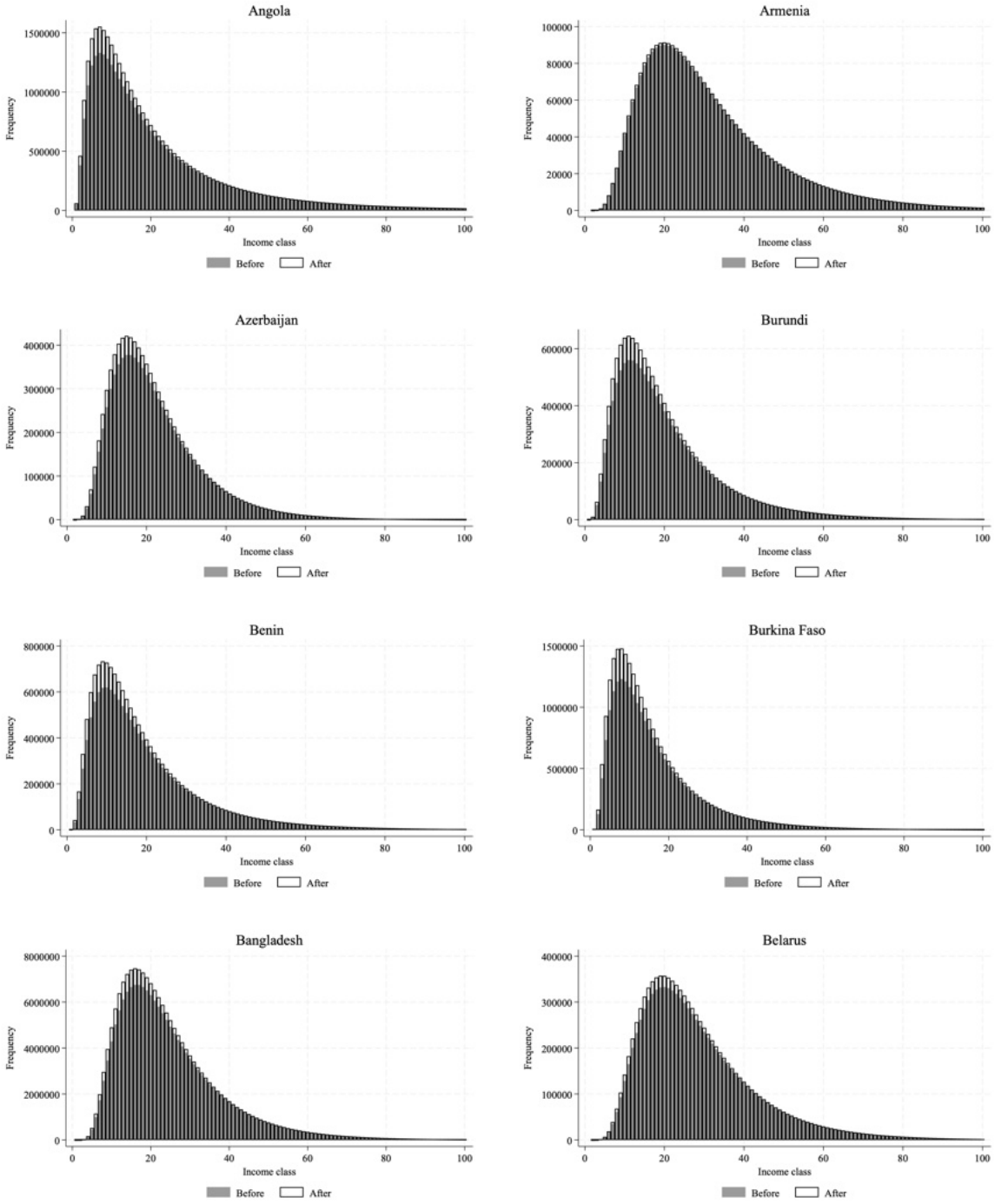


Table A.7: Distribution of income class before and after correction

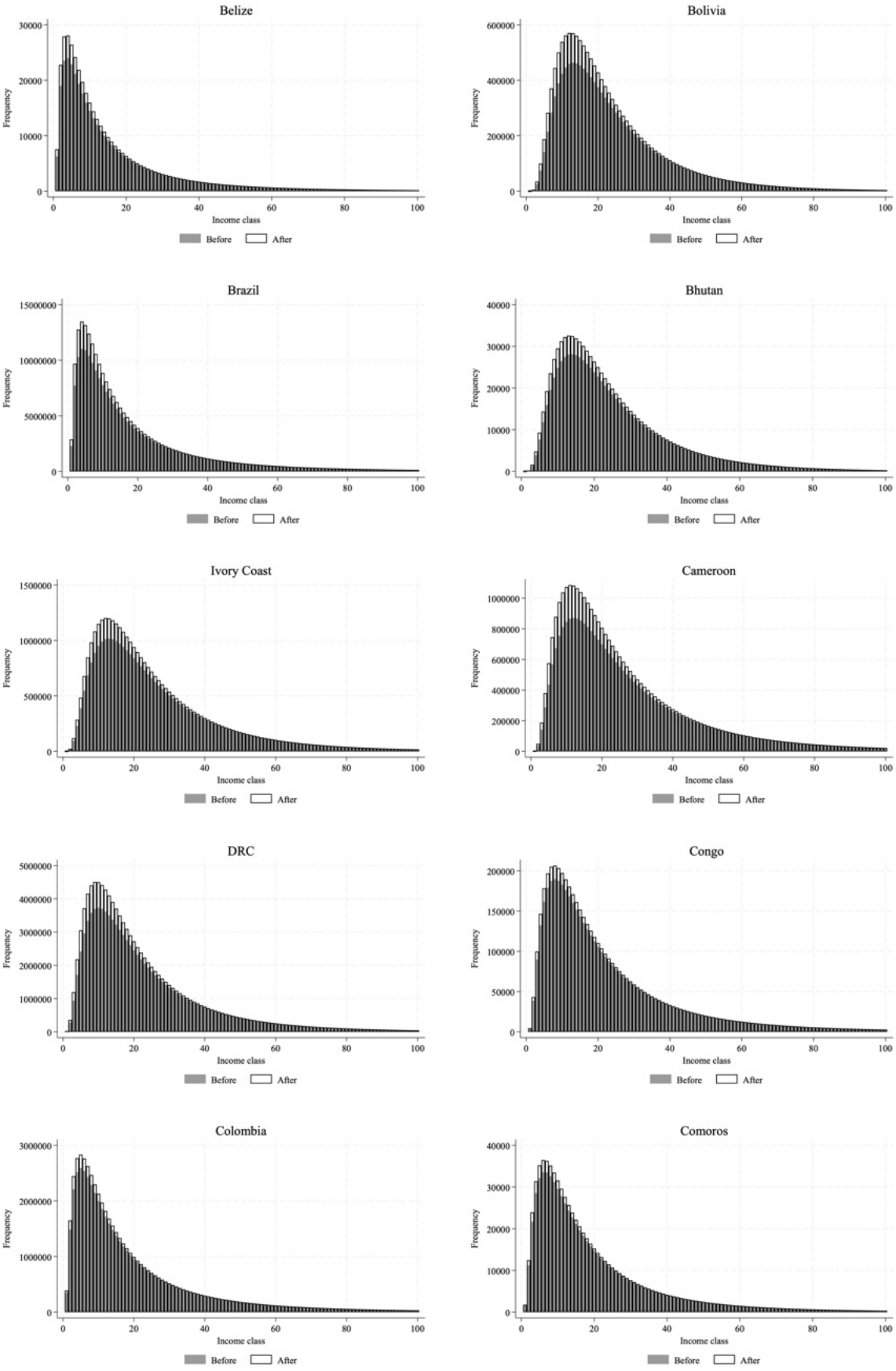


Table A.7: Distribution of income class before and after correction

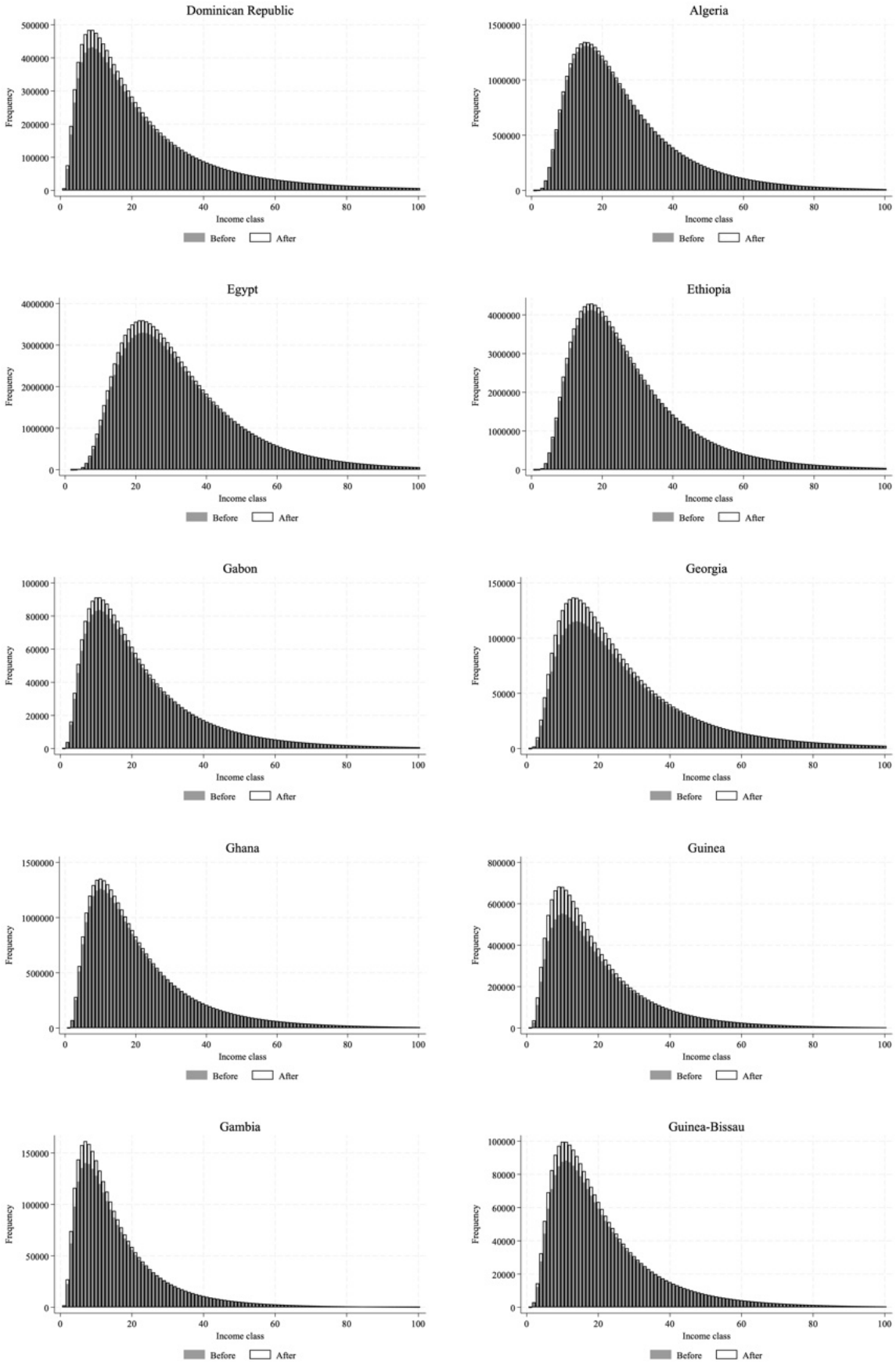


Table A.7: Distribution of income class before and after correction

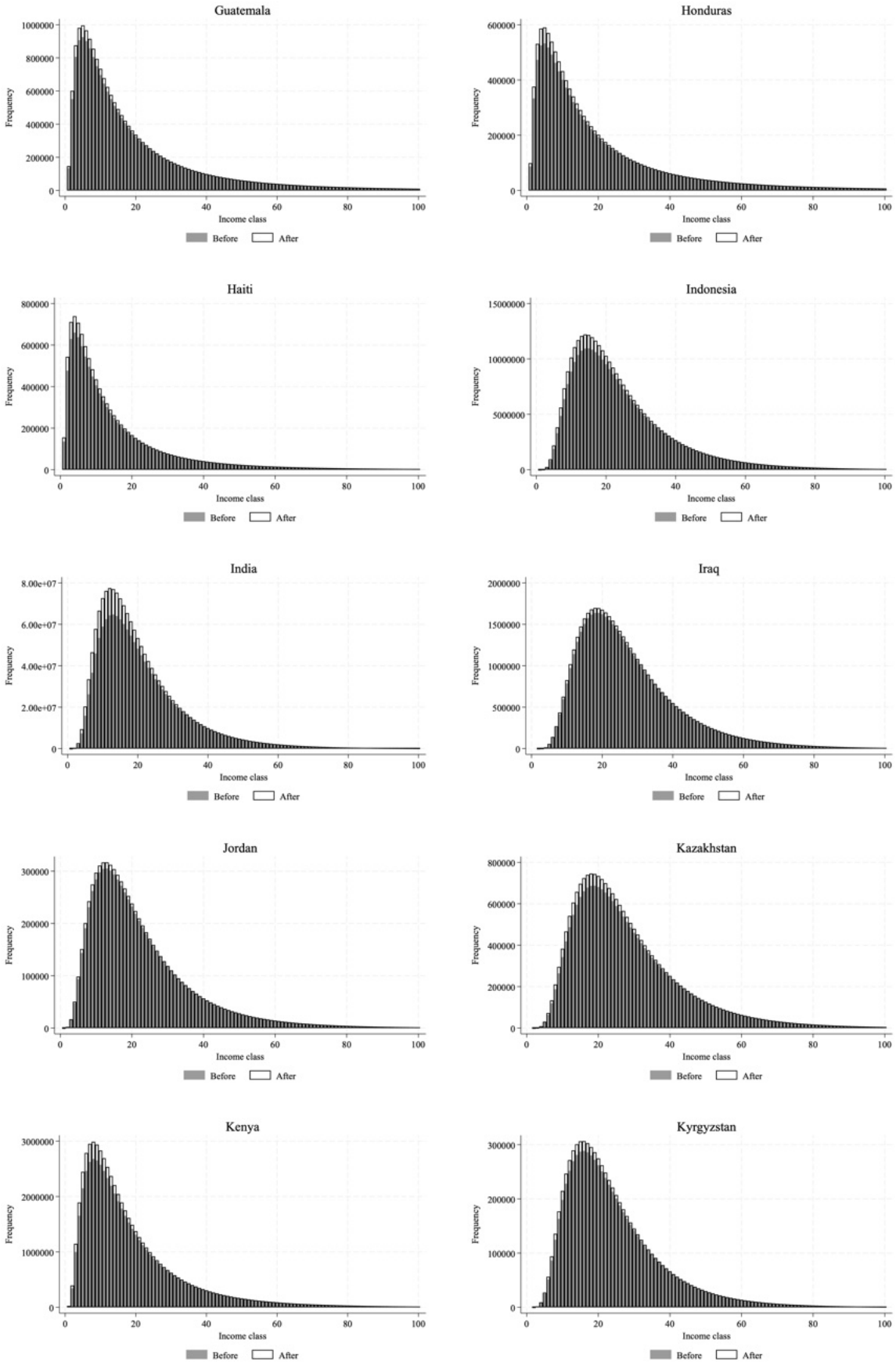


Table A.7: Distribution of income class before and after correction

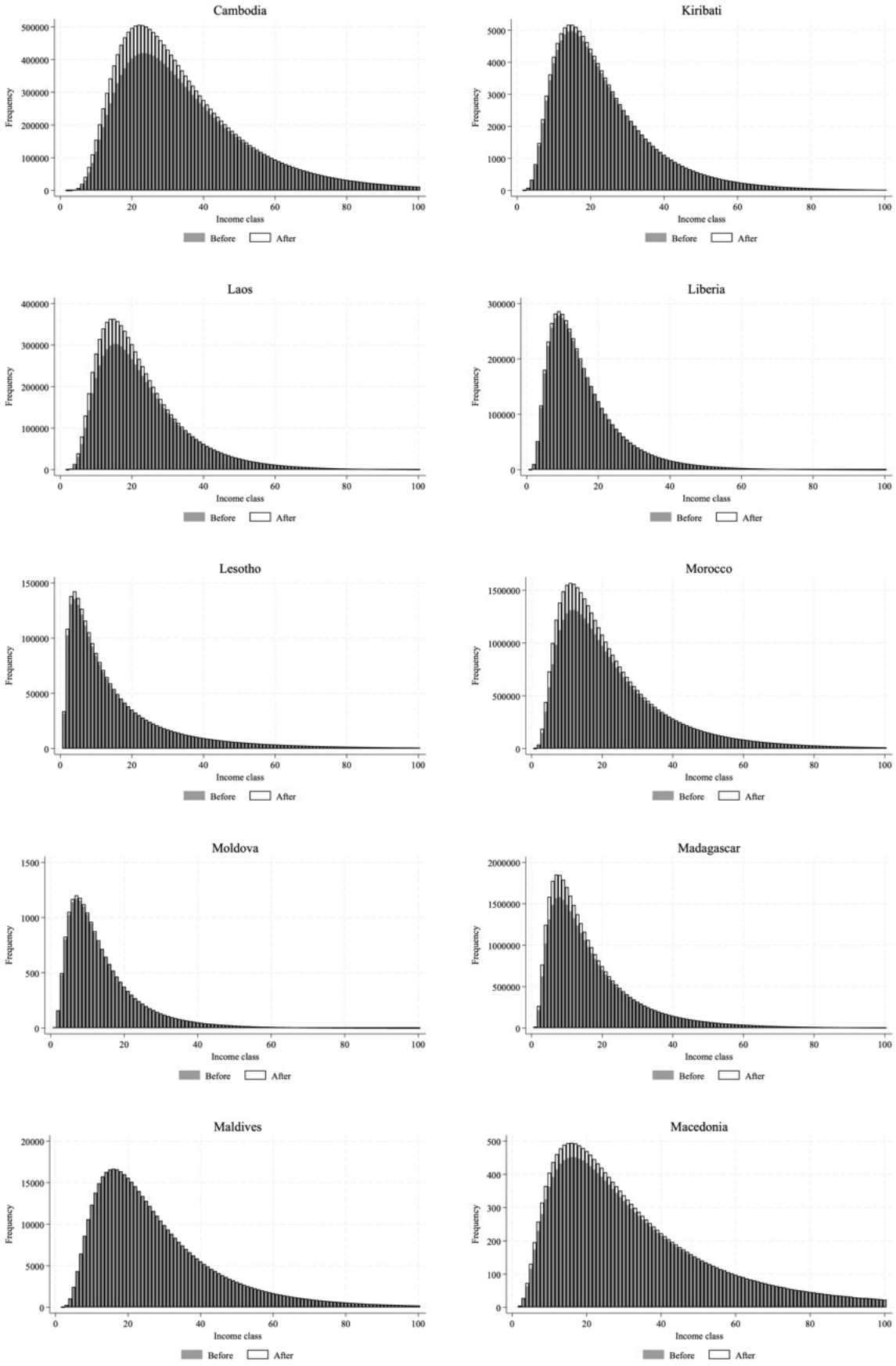


Table A.7: Distribution of income class before and after correction

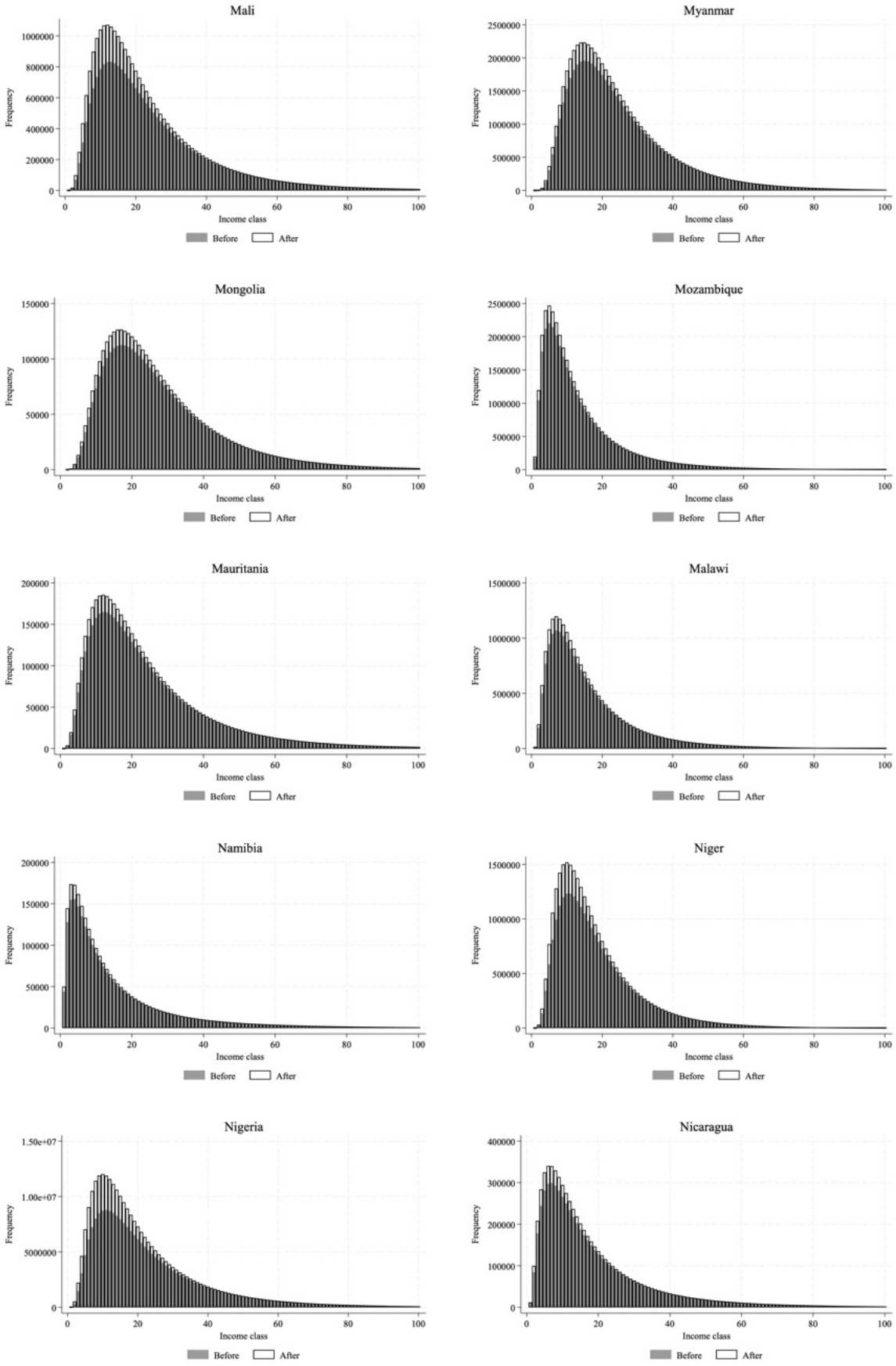


Table A.7: Distribution of income class before and after correction

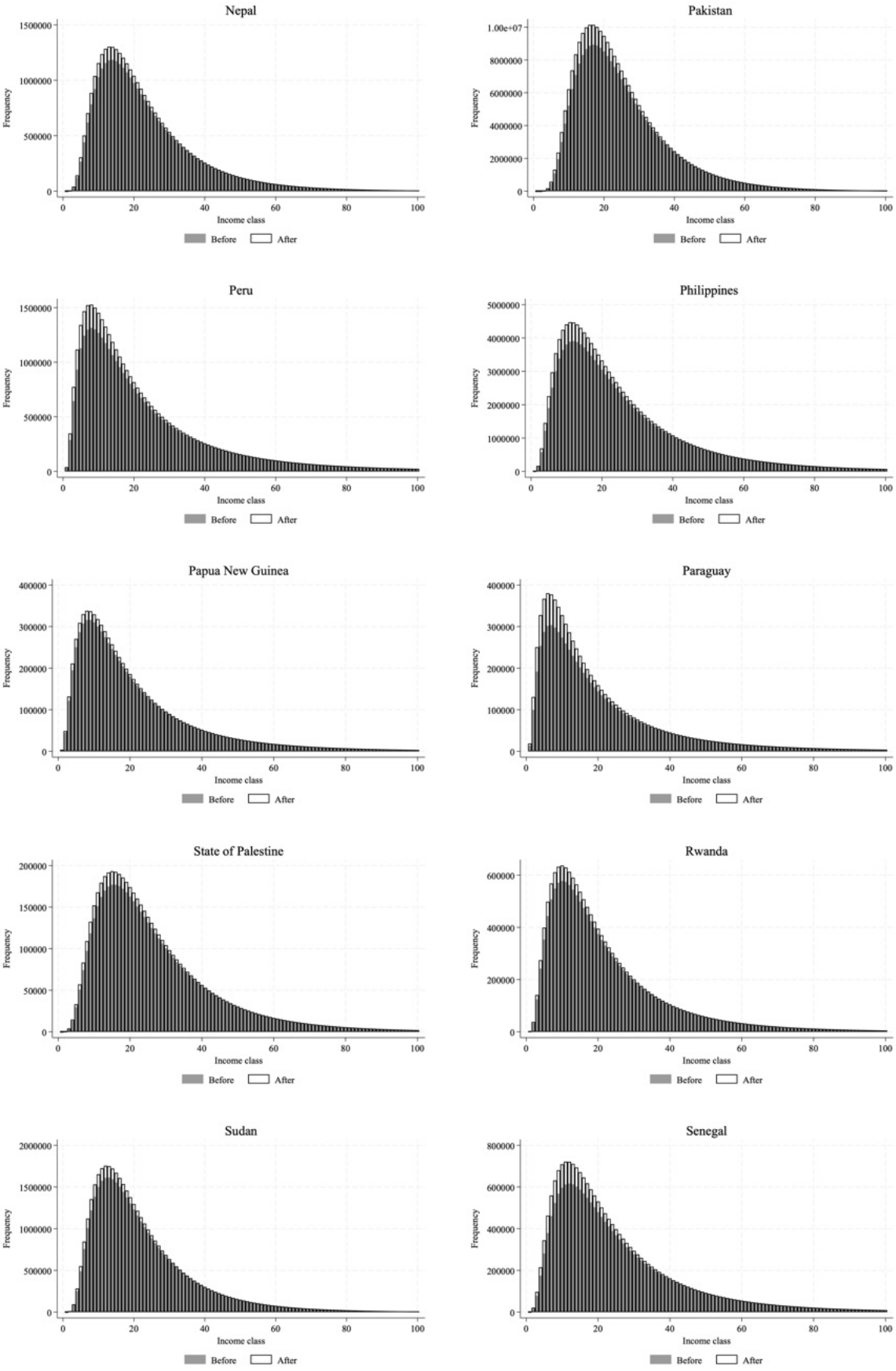


Table A.7: Distribution of income class before and after correction

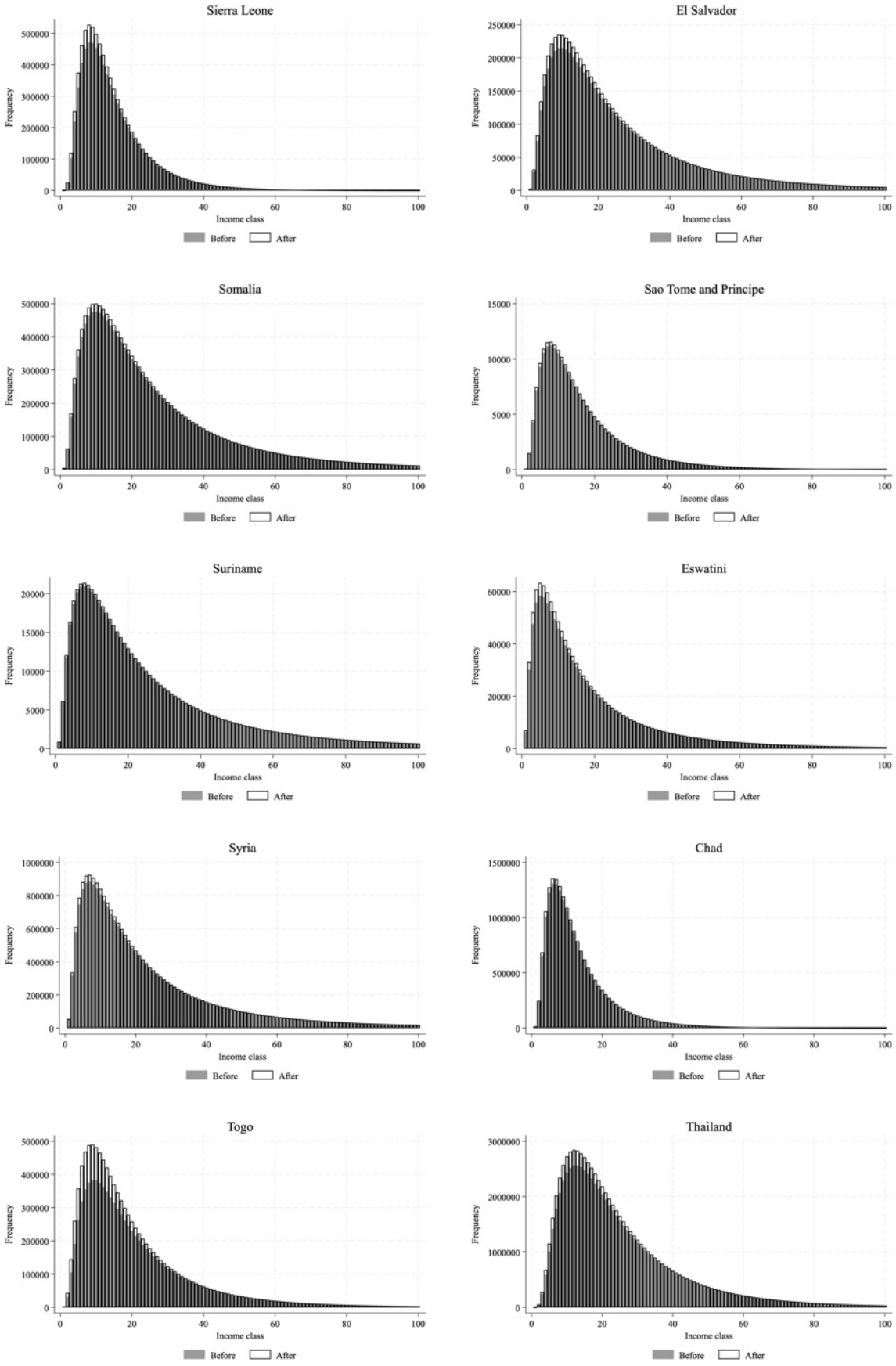


Table A.7: Distribution of income class before and after correction

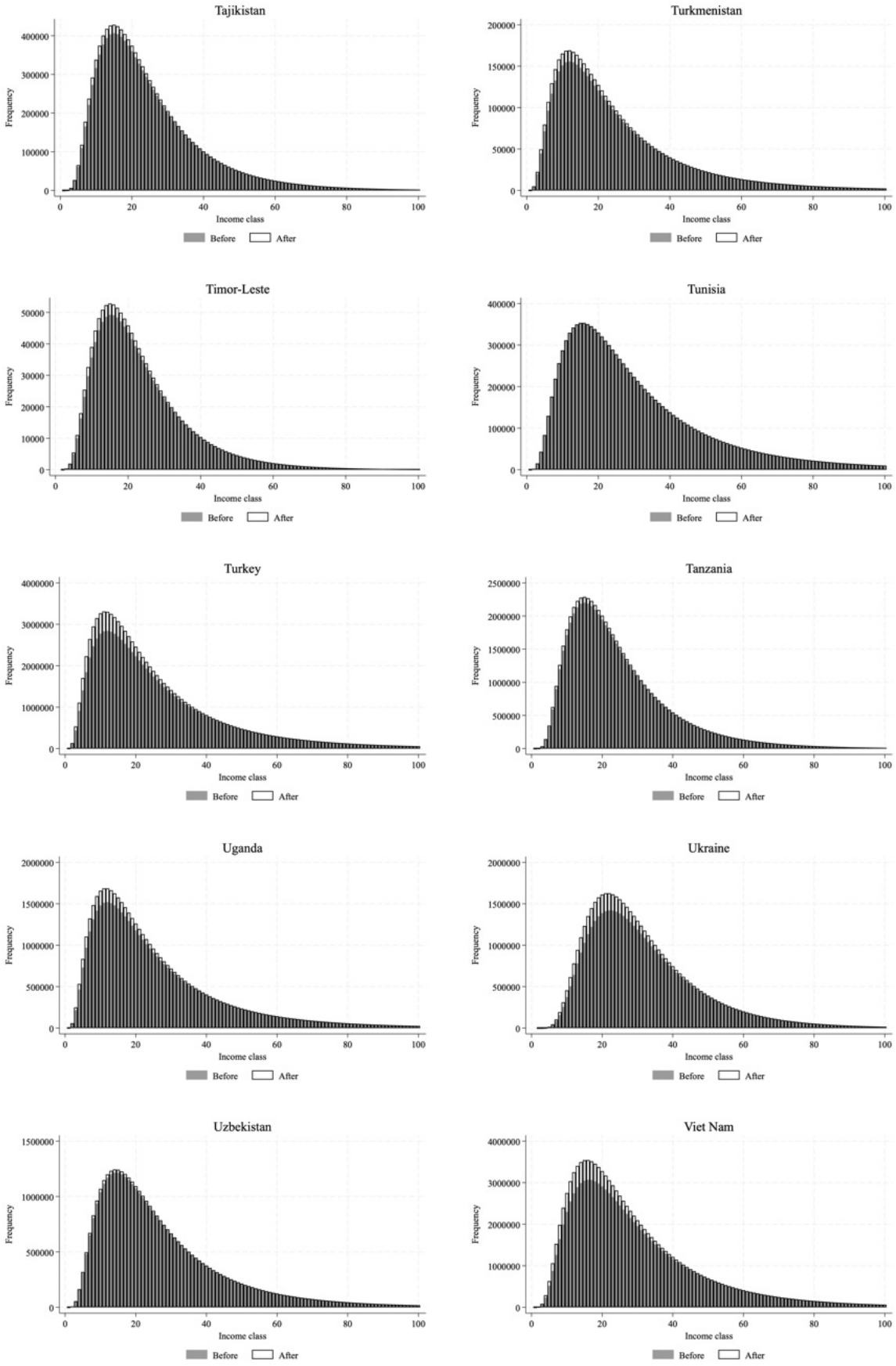
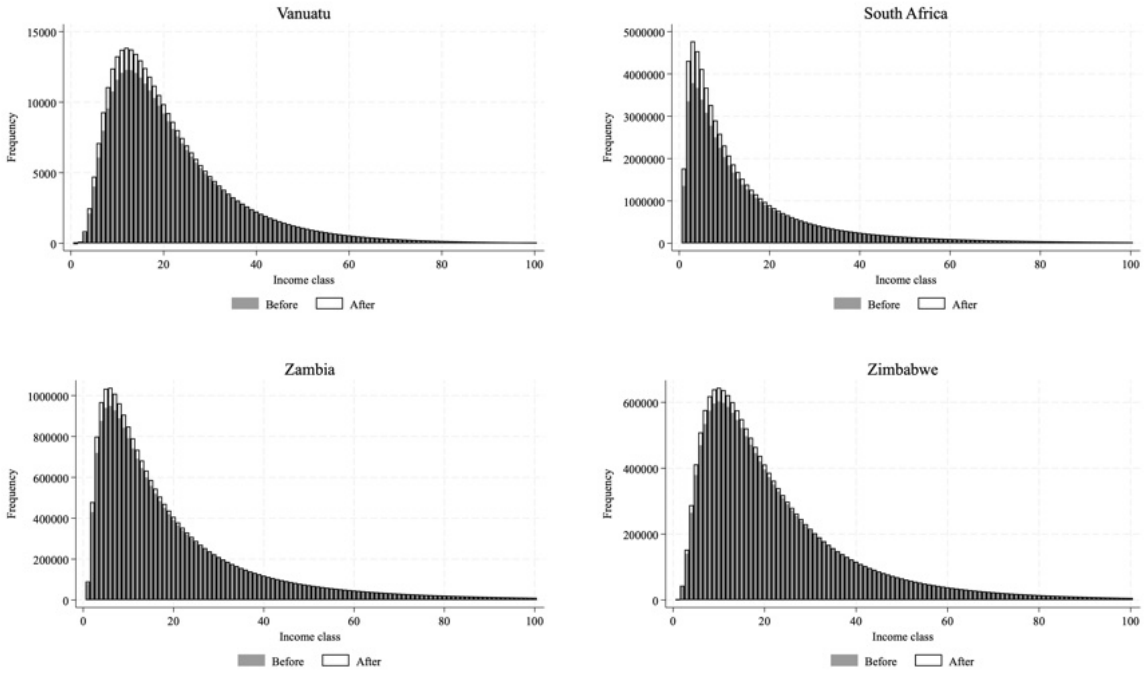


Table A.7: Distribution of income class before and after correction



A.7 Counting the missing poor

Table A.8: Populations: observed, estimated and corrected

	Population				Correction		
	Observed	Estimated	Diff. (obs-est)		Pop. corrected	Diff. (est-cor)	
			#	%		#	%
Algeria	37,029,650	36,753,325	276,325	0.7	37,447,357	694,032	1.9
Angola	31,480,496	30,753,716	726,780	2.3	33,782,586	3,028,870	9.8
Armenia	2,964,300	2,931,248	33,052	1.1	2,961,229	29,981	1.0
Azerbaijan	8,391,850	8,385,113	6,737	0.1	9,057,442	672,329	8.0
Bangladesh	169,384,897	169,013,391	371,506	0.2	181,422,579	12,409,188	7.3
Belarus	9,379,952	9,348,042	31,910	0.3	9,845,355	497,313	5.3
Belize	381,347	373,690	7,657	2.0	410,366	36,676	9.8
Benin	13,672,980	13,593,469	79,511	0.6	15,147,382	1,553,913	11.4
Bhutan	780,914	773,708	7,206	0.9	853,668	79,960	10.3
Bolivia	12,244,159	12,151,982	92,177	0.8	13,969,937	1,817,955	15.0
Brazil	211,140,729	204,615,424	6,525,305	3.1	229,593,195	24,977,772	12.2
Burkina Faso	22,339,486	22,277,194	62,292	0.3	25,161,414	2,884,220	12.9
Burundi	12,669,303	12,622,300	47,003	0.4	13,857,527	1,235,227	9.8
Cambodia	15,396,772	15,143,670	253,102	1.6	17,284,244	2,140,574	14.1
Cameroon	27,396,157	26,652,954	743,203	2.7	30,660,145	4,007,191	15.0
Chad	18,455,316	18,441,048	14,268	0.1	18,874,208	433,160	2.3
Colombia	52,321,152	50,917,845	1,403,307	2.7	53,699,871	2,782,026	5.5
Comoros	711,503	699,565	11,938	1.7	735,902	36,337	5.2
Congo	4,697,310	4,596,069	101,241	2.2	4,846,706	250,637	5.5
Cote d'Ivoire	30,206,186	29,698,616	507,570	1.7	33,131,229	3,432,613	11.6
DRC	95,989,998	94,593,225	1,396,773	1.5	106,744,705	12,151,480	12.8
Dominican Republic	11,427,557	11,160,122	267,435	2.3	11,990,786	830,664	7.4
Egypt	112,236,164	110,970,745	1,265,419	1.1	117,988,752	7,018,007	6.3
El Salvador	6,309,624	6,108,920	200,704	3.2	6,454,488	345,568	5.7
Eswatini	1,150,984	1,127,052	23,932	2.1	1,181,879	54,827	4.9
Ethiopia	122,138,588	121,155,617	982,971	0.8	124,565,391	3,409,774	2.8
Gabon	2,156,900	2,131,752	25,148	1.2	2,258,007	126,255	5.9
Gambia	2,520,555	2,511,180	9,375	0.4	2,745,076	233,896	9.3
Georgia	3,673,850	3,597,293	76,557	2.1	4,023,056	425,763	11.8
Ghana	29,845,451	29,596,628	248,823	0.8	30,994,659	1,398,031	4.7
Guatemala	18,124,838	17,667,700	457,138	2.5	18,463,338	795,638	4.5
Guinea	12,869,560	12,772,329	97,231	0.8	14,666,121	1,893,792	14.8
Guinea-Bissau	2,093,857	2,080,307	13,550	0.6	2,255,602	175,295	8.4
Haiti	10,069,771	9,934,711	135,060	1.3	10,623,693	688,982	6.9
Honduras	10,825,703	10,490,134	335,569	3.1	11,154,062	663,928	6.3
India	1,432,758,115	1,430,084,481	2,673,634	0.2	1,617,499,755	187,415,280	13.1
Indonesia	283,487,931	282,229,568	1,258,363	0.4	303,891,257	21,661,688	7.7
Iraq	45,074,049	44,923,808	150,241	0.3	46,069,986	1,146,178	2.6
Jordan	7,341,054	7,310,605	30,449	0.4	7,505,352	194,747	2.7
Kazakhstan	19,743,603	19,648,648	94,955	0.5	20,814,568	1,165,920	5.9

Table A.8: Populations: observed, estimated and corrected

	Population				Correction		
	Observed	Estimated	Diff. (obs-est)		Pop. corrected	Diff. (est-cor)	
			#	%		#	%
Kenya	54,980,444	54,616,500	363,944	0.7	58,563,638	3,947,138	7.2
Kiribati	124,509	124,090	419	0.3	127,582	3,492	2.8
Kyrgyzstan	7,099,750	7,084,660	15,090	0.2	7,399,900	315,240	4.4
Lao	7,174,073	7,161,922	12,151	0.2	8,139,946	978,024	13.7
Lesotho	2,160,819	2,121,349	39,470	1.8	2,184,898	63,549	3.0
Liberia	4,755,608	4,751,651	3,957	0.1	4,842,670	91,019	1.9
Macedonia	1,876,262	1,839,387	36,875	2.0	1,956,493	117,106	6.4
Madagascar	30,250,717	30,109,417	141,300	0.5	33,363,162	3,253,745	10.8
Malawi	19,183,274	19,106,250	77,024	0.4	20,536,708	1,430,458	7.5
Maldives	496,363	491,387	4,976	1.0	493,041	1,654	0.3
Mali	22,778,516	22,533,756	244,760	1.1	26,598,459	4,064,703	18.0
Mauritania	4,547,162	4,491,374	55,788	1.2	4,853,399	362,025	8.1
Moldova	2,457,783	2,427,624	30,159	1.2	2,464,218	36,594	1.5
Mongolia	3,433,748	3,401,013	32,735	1.0	3,685,721	284,708	8.4
Morocco	33,996,176	33,682,300	313,876	0.9	37,805,977	4,123,677	12.2
Mozambique	32,734,559	32,582,438	152,121	0.5	34,939,398	2,356,960	7.2
Myanmar	51,894,938	51,639,358	255,580	0.5	56,545,118	4,905,760	9.5
Namibia	2,391,827	2,346,210	45,617	1.9	2,501,062	154,852	6.6
Nepal	29,705,025	29,576,934	128,091	0.4	31,587,595	2,010,661	6.8
Nicaragua	6,066,492	5,995,119	71,373	1.2	6,493,706	498,587	8.3
Niger	24,907,057	24,859,005	48,052	0.2	28,545,016	3,686,011	14.8
Nigeria	226,510,651	223,940,512	2,570,139	1.1	273,810,925	49,870,412	22.3
Pakistan	228,864,896	228,326,992	537,904	0.2	250,213,789	21,886,796	9.6
Papua New Guinea	7,558,585	7,447,559	111,026	1.5	7,761,432	313,873	4.2
Paraguay	6,929,153	6,774,469	154,684	2.2	7,752,961	978,492	14.4
Peru	34,217,848	33,278,595	939,253	2.7	36,511,673	3,233,078	9.7
Philippines	114,891,199	112,638,656	2,252,543	2.0	122,924,152	10,285,496	9.1
Rwanda	14,187,085	14,039,365	147,720	1.0	14,944,101	904,736	6.4
Sao Tome and Principe	206,970	206,230	740	0.4	210,299	4,069	2.0
Senegal	17,526,335	17,251,209	275,126	1.6	19,114,485	1,863,276	10.8
Sierra Leone	7,554,563	7,550,099	4,464	0.1	8,125,889	575,790	7.6
Somalia	14,348,740	13,859,431	489,309	3.4	14,292,864	433,433	3.1
South Africa	56,531,658	55,162,589	1,369,069	2.4	62,872,704	7,710,115	14.0
State of Palestine	5,165,775	5,118,493	47,282	0.9	5,427,690	309,197	6.0
Sudan	38,823,318	38,663,028	160,290	0.4	40,921,555	2,258,527	5.8
Suriname	623,164	592,038	31,126	5.0	598,496	6,458	1.1
Syria	22,462,173	21,655,775	806,398	3.6	22,277,347	621,572	2.9
Tajikistan	10,590,927	10,545,450	45,477	0.4	10,933,605	388,155	3.7
Tanzania	57,294,405	57,048,360	246,045	0.4	58,620,650	1,572,290	2.8
Thailand	71,702,435	70,791,537	910,898	1.3	75,749,792	4,958,255	7.0
Timor-Leste	1,181,903	1,179,675	2,228	0.2	1,238,704	59,029	5.0
Togo	9,011,535	8,921,142	90,393	1.0	10,435,849	1,514,707	17.0

Table A.8: Populations: observed, estimated and corrected

	Population				Correction		
	Observed	Estimated	Diff. (obs-est)		Pop. corrected	Diff. (est-cor)	
			#	%		#	%
Tunisia	12,064,886	11,774,574	290,312	2.4	11,780,903	6,329	0.1
Turkey	84,979,913	83,153,209	1,826,704	2.1	91,664,586	8,511,377	10.2
Turkmenistan	4,410,507	4,341,652	68,855	1.6	4,583,372	241,720	5.6
Uganda	43,932,447	43,149,157	783,290	1.8	46,168,714	3,019,557	7.0
Ukraine	44,680,014	44,403,310	276,704	0.6	49,018,379	4,615,069	10.4
Uzbekistan	36,361,859	35,881,153	480,706	1.3	36,442,191	561,038	1.6
Vanuatu	293,428	292,202	1,226	0.4	316,524	24,322	8.3
Viet Nam	99,680,655	98,048,089	1,632,566	1.6	108,020,389	9,972,300	10.2
Zambia	20,152,938	19,681,582	471,356	2.3	20,784,661	1,103,079	5.6
Zimbabwe	15,271,368	15,075,069	196,299	1.3	15,729,312	654,243	4.3