Inequality and Poverty in Africa: Regional Updates and Estimation of a Panel of Income Distributions

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INEQUALITY AND POVERTY IN AFRICA: REGIONAL UPDATES AND ESTIMATION OF A PANEL OF INCOME DISTRIBUTIONS

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Abstract

The African region is of critical importance in the context of global poverty and inequality. Over the last two decades, there has been uneven growth performance among countries from the region. Africa is the only region where the number of absolutely poor, as measured by the World Bank's international poverty lines of $1/day and $2/day, has been increasing over the last two decades. A key determining factor is the extent of inequality and the nature of income distributions among African nations. With the availability of 2005 and 2011 purchasing power parity and per capita real income data from the International Comparison Program (ICP) and increased coverage and availability of country-specific income distribution data over recent years, it is now possible to update previous work investigating changes in inequality and poverty in Africa. Chotikapanich et al (2012) estimated global and regional inequalities for 1993 and 2000. Warner et al (2013) extend the results to include those for 2005 by making use of purchasing power parity data from the 2005 ICP round. The present paper has two objectives. First objective is to update previous estimates for inequality and poverty in Africa for 1993, 2000 and 2005 and to extend the estimates to include results for 2010. Second objective, given the importance of the effect of the global financial crisis on Africa (Milanovic 2009), is to compile a panel of income distributions for a large number of countries in Africa for the years between 1997 and 2010. Where annual country-specific income distribution data are available, we fit mixtures of lognormal distributions to that data. To overcome data unavailability for some country-year combinations, we develop a technique to interpolate and extrapolate income distributions for years and countries for which no data are available. Extensive and comprehensive analysis is done on the change in income distributions, inequality and poverty for the region as a whole and for relative movements between countries in the region.

JEL classification numbers: C13, C16, D31

Key words: Income distributions; inequality; mixtures; lognormal distribution; Kullback-Liebler distance; extrapolation

1. Introduction

A closer economic integration and increased globalization of the regions of the world has resulted in impressive growth performance of countries in the Asian and African region. Africa [1] is now considered as the fastest growing region. The Sub-Saharan Africa posted a 4.9 percent growth in GDP in 2013 and projected to grow at 5.3 per cent in 2014. There are six African economies, Angola, Nigeria, Ethiopia, Chad, Mozambique and Rawanda, among the top ten fastest growing economies in the world during the period 2000 to 2010. There are seven African countries in the top ten fastest growing economies over the period 2011 to 2015 with Ethiopia as the top performing nation in the world behind China and India. However, during the same period inequality in the distribution of income has been on the increase. Gini coefficient for the African region increased from 0.42 to o.46 over the period 2000 to 2010 (African Development Bank, 2012[2]). Despite this impressive growth performance, poverty in Africa is at a high level. Chen and Ravallion (2010) report that 50.9 percent of population in Sub-Saharan Africa are under absolute poverty with 390.6 million living under $1.25 per day in 2005. Nearly 80.5 percent of population in Africa living under $2.50 per day. While global poverty has reduced from 1.896 billion under $1.25 per day in 1981 to 1.376 billion in 2005, during the same period, number of poor in Sub-Saharan Africa has increased from 213.7 million to 390.6 million in 2005. A key determining factor is the extent of inequality and the nature of income distributions among African nations.

At a global level, associated with the aspects of growth and globalization have been concerns about whether inequality and welfare have been increasing or decreasing, whether there has been a reduction in poverty and whether growth has favoured the poor relative to the rich (Bhalla (2002, 2004), Chotikapanich et al (2012), Milanovic, (2002, 2005), Sala-i-Martin (2006), Dowrick and Akmal (2005)). Further, there is a concern that increasing globalization and accompanying economic growth may increase inequality, and may fail to achieve desired levels of poverty reduction. It is therefore important to monitor growth performance as well as changes in income distributions at a country, regional and global level. In Africa, significant growth has been achieved over the last decade. However, inequality over the period has been increasing (Warner et al., 2013). Chen and Ravallion (2010) report an increase in the number of absolute poor in the region over the last two decades. Tracking changes in inequality, welfare, poverty and pro-poor growth on national, regional, and global levels requires data on internationally comparable real income data as well as income distribution data for as many countries as possible, and as frequently as possible.

Economic performance of nations and welfare enjoyed by individuals in different countries are assessed using levels and trends in real per capita income. The size of the economies is measured

[1] For the purpose of this paper, Africa refers to Sub-Saharan Africa.
[2] http://www.afdb.org/fileadmin/uploads/afdb/Documents/Policy-Documents/FINAL%20Briefing%20Note%205%20Income%20Inequality%20in%20Africa.pdf

using real gross domestic product (GDP) expressed in PPP (*purchasing power parity)* terms. Data on real per capita income in PPP dollars are available from the International Comparison Program (ICP) which is conducted world-wide roughly once in five years. The non-availability of real per capita income data is addressed through the extrapolations of real per capita income in PPP terms provided by the Penn World Table (PWT) (Summers and Heston, 1991; Summers, Heston and Aten, 2003; and Feenstra et al., 2013), World Development Indicators (World Bank, various years) and more recently by UQICD (Rao et al, 2010, 2013). It has long been recognised that size of the economy and real per capita income are not sufficient to assess welfare of the people in different countries. Since Sen (1976), it is widely accepted that the distribution of income in the country along with the size of the economy as measured by real GDP must be jointly considered. Sen recommended the use of movements in real per capita income adjusted for changes in the distribution of income in the country as a measure of social welfare. While annual data on real per capita GDP in PPP terms are available for more than 150 countries and over the period 1970 to 2010, income distribution data are limited in their availability which is evident from the WIDER and World Bank data sources. This paper seeks to fill this gap.

The two main sources of income distribution data are the *World Income Inequality Database* compiled by the World Institute for Development Economic Research (UNU-WIDER, 2008)), and the data compiled by the World Bank for its PovcalNet website (World Bank, 2012), with the latter focusing on developing countries. Researchers around the world rely on these two sources for quantitative and qualitative assessment of the effects of inequality on macroeconomic performance and their microeconomic impact for the households. Brandolini and Atkinson (2003) provide an assessment on the volume and quality of income distribution data available for researchers. A major constraint experienced by researchers is the limitations in coverage and in the detail of information provided. The WIDER data are available in the form of income shares of quintile or decile groups of population for different countries, and in some cases only estimates of the Gini coefficient are available. The World Bank data is generally available as 20 income share groups but the country coverage is much more limited. The years for which the WIDER and World Bank data are available coincide with the years when household expenditure surveys are conducted, typically once every five years, but less frequently in many cases, and with no international synchronization, making it difficult to assess regional or global measurement for a particular year. For both sources, the region where the data have less coverage and are less available is Africa. In this paper, we concentrate on this region.

The aim of this paper is to develop methodology for using available data to estimate *annual* income distributions, and to use these distributions to track inequality, welfare, poverty and pro-poor growth on an annual basis. We then apply the methodology to correct the data deficiency for Africa by compiling a panel of income distributions covering a large number of countries and the 14-year period from 1997 to 2010. The panel of data is obtained by fitting income distributions to the available data and then, using econometric methods for interpolation and extrapolation that we develop, we estimate income distributions for countries and years for which there is no currently available data. These distributions are then used to develop comprehensive measures of inequality, welfare, poverty, and pro-poor growth, nationally and regionally, from 1997 to 2010.

Monitoring progress towards the first Millennium Development Goal of halving the number of people under the \$1/day poverty line, the World Bank uses their data to provide estimates of global, regional and country-specific poverty under \$1/day (Chen and Ravallion, 2010). They estimate parametric Lorenz curves and use the relationship between Lorenz curves and income distributions to estimate a number of poverty measures. We improve on their work by directly estimating income distributions and by providing estimates for more years and more countries in Africa. The range of incomes for which a Lorenz curve has a valid income distribution is limited. Direct estimation of income distributions overcomes this problem (Chotikapanich et al, 2013).

Previous work on estimating national, regional and global income distributions from the World Bank or WIDER data includes Milanovic (2002), Sala-i-Martin (2006), Pinkovsky and Sala-i-Martin (2009) and Chotikapanich et al (2012). Milanovic compares the world income distributions in 1988 and 1993, obtained by aggregating country-level income shares in those or nearby years. In his early papers, Sala-i-Martin made use of kernel smoothing and linear interpolation of income shares to extrapolate available income distribution to a large number of countries and the period 1970 to 2000. Given the questionable validity of using kernel density estimation on only five points, namely the income shares for quintile groups, Pinkovsky and Sala-i-Martin (2009) fit lognormal distributions to the available data. They also abandon the linear interpolation of income shares and make use of extrapolation based on Gini coefficient data. However, their estimation techniques are not optimal, the lognormal distribution has been shown to be inferior relative to more general distributions, and their extrapolation techniques and assumptions for countries with missing data are somewhat ad hoc. Other work is that of Chotikapanich et al (2012) who estimate beta-2 income distributions for 91 countries for years at or close to 1993 and 2000 and use these distributions to form regional and global income distributions. We improve on these past studies by: (i) using optimal generalized method of moments (GMM) estimation of mixture distributions for years where data are available; and (ii) proposing more rigorous methods for extrapolation and interpolation.

The remainder of the paper is organized as follows. Section 2 briefly describes our methodology, including specification and estimation of the lognormal mixture distributions for the countries and years where there are data available. This section also includes the description of how to model regional income distribution, and computation of inequality measures, their decompositions and poverty measures based on the mixture of lognormal income distribution. Details of how the interpolation and extrapolation are done are given in Section 3. Details of the data used and the coverage are given in Section 4. The empirical results are presented in Section 5. Section 6 contains a summary of the contribution of the paper.

2. Estimation of income distributions for countries/years where data are available

Typically historical data on income distributions are available from published sources and are usually in an aggregated form. In most cases income shares of decile groups of population are provided along with estimates of average income for the whole population. Hajargasht et al (2012) developed a methodology for estimating income distributions from data in grouped form. They derive the components necessary for GMM estimation of income distributions (see Hajargasht et al., 2012) from grouped data in the form of population and income shares. General expressions for the moments and weight matrix required for any assumed distribution are also derived, and then specified for special cases such as the generalized beta distribution and its special case distributions (beta, Singh-Maddala, Dagum), the generalized gamma distribution, and the lognormal distribution. With a view to finding a more flexible distribution, in a subsequent paper, Griffiths and Hajargasht (2012) specified the required conditions for a mixture of lognormal distributions and showed the superiority of the mixture over the earlier choices. This methodology is used in the current paper to obtain GMM estimates of lognormal mixture distributions for all countries/years for which data are available.

To briefly summarize the estimation technique, we begin with a sample of N observations $\left(y_1, y_2, \ldots, y_N\right)$, assumed to be randomly drawn from a parametric income distribution $f\left(y;\boldsymbol{\phi}\right)$ where $\boldsymbol{\phi}$ is a vector of unknown parameters. These observations have been grouped into I income classes $(z_0, z_1), (z_1, z_2), \ \ldots, (z_{I-1}, z_I)$, with $z_0 = 0$ and $z_I = \infty$. The available data are the class mean incomes $\bar{y}_1, \bar{y}_2, \ldots, \bar{y}_I$, the proportions of observations in each class $c_1, c_2, \ldots, c_I$, and the income shares for each income class $s_1, s_2, \ldots, s_I$. The estimation problem is to estimate $\boldsymbol{\phi}$, along with the unknown class limits $\mathbf{z}' = \left(\boldsymbol{z}_1, \boldsymbol{z}_2, \ldots, \boldsymbol{z}_{I-1}\right)$ which are typically unknown.

To facilitate the estimation we define the indicator functions

$$g_i\left(y\right) = \begin{cases} 1 & \text{if} \quad z_{i-1} < y < z_i \\ 0 & \text{otherwise} \end{cases} \qquad \text{for } i = 1, 2, \ldots, I \tag{1}$$

The proportion of population c_i and the class mean income $\bar{y}_i$ can be written as

$$c_i = \frac{N_i}{N} = \frac{1}{N}\sum_{n=1}^{N} g_i\left(y_n\right) \tag{2}$$

$$\bar{y}_i = \frac{s_i \bar{y}}{c_i} = \frac{1}{N_i}\sum_{n=1}^{N} y_n g_i\left(y_n\right) \tag{3}$$

In terms of estimation, it is more convenient to use $\tilde{y}_i$ where

$$\tilde{y}_i = c_i \bar{y}_i = \frac{1}{N}\sum_{n=1}^{N} y_n g_i\left(y_n\right) \tag{4}$$

The GMM estimator is given by

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \mathbf{H}\left(\boldsymbol{\theta}\right)'\boldsymbol{\Omega}\,\mathbf{H}\left(\boldsymbol{\theta}\right) \tag{5}$$

where $\boldsymbol{\theta}' = (\boldsymbol{\phi}', \mathbf{z}')$ contains the unknown parameters of the income distribution including the unknown class limits. $\mathbf{H}(\boldsymbol{\theta})$ is a set of moments constructed for c_i and $\tilde{y}_i$ such that the moment conditions $E\left[\mathbf{H}(\boldsymbol{\theta})\right] = \mathbf{0}$ are suitable for estimating $\boldsymbol{\theta}$, and $\boldsymbol{\Omega}$ is the weight matrix.

Equations (2) and (4) define sample moments for the sample proportion within each income class, and the income class "means". The corresponding population moments for c_i and $\tilde{y}_i$ can be defined respectively as:

$$k_i\left(\boldsymbol{\theta}\right) = \int_0^\infty g_i\left(y\right) f\left(y;\boldsymbol{\phi}\right)dy = E\left[g_i\left(y\right)\right] \tag{6}$$

$$m_i\left(\boldsymbol{\theta}\right) = \int_0^\infty y g_i\left(y\right) f\left(y;\boldsymbol{\phi}\right)dy = E\left[y g_i\left(y\right)\right] \tag{7}$$

The moment conditions are $E\left(c_i - k_i\right) = 0$ and $E\left(\tilde{y}_i - m_i\right) = 0$. The matrix $\mathbf{H}(\boldsymbol{\theta})$ in equation (5) is defined by these moments. See Hajargasht et al (2012) for details of specification of $\mathbf{H}(\boldsymbol{\theta})$ and the weight matrix $\boldsymbol{\Omega}$. After setting up the GMM objective function using the optimal weight matrix, Hajargasht et al (2012) show that it can be written as:

$$\mathbf{H}'\boldsymbol{\Omega}\mathbf{H} = \sum_{i=1}^{N}\omega_{1i}(c_i - k_i)^2 + \sum_{i=1}^{N}\omega_{2i}(\tilde{y}_i - m_i)^2 - 2\sum_{i=1}^{N}\omega_{3i}(c_i - k_i)(\tilde{y}_i - m_i) \tag{11}$$

where $\omega_{1i} = m_i^{(2)}/v_i$, $\omega_{2i} = k_i/v_i$, $\omega_{3i} = m_i/v_i$, $v_i = k_i m_i^{(2)} - m_i^2$, and

$$m_i^{(2)}\left(\boldsymbol{\theta}\right) = \int_{z_{i-1}}^{z_i} y^2 f(y;\boldsymbol{\phi})dy = \int_0^\infty y^2 g_i\left(y\right) f\left(y;\boldsymbol{\phi}\right)dy = E\left[y^2 g_i\left(y\right)\right]$$

To estimate $\boldsymbol{\theta}$ using $\mathbf{H}'\boldsymbol{\Omega}\mathbf{H}$ we need to specify k_i, m_i and $m_i^{(2)}$ in terms of the parameters $\boldsymbol{\phi}$ and the unknown class limits z_i. They are:

$$k_i\left(\boldsymbol{\theta}\right) = F(z_i;\boldsymbol{\phi}) - F(z_{i-1};\boldsymbol{\phi}) \tag{12}$$

$$m_i\left(\boldsymbol{\theta}\right) = \mu\left(F^{(1)}(z_i;\boldsymbol{\phi}) - F^{(1)}(z_{i-1};\boldsymbol{\phi})\right) \tag{13}$$

$$m_i^{(2)}\left(\boldsymbol{\theta}\right) = \mu^{(2)}\left[F^{(2)}(z_i;\boldsymbol{\phi}) - F^{(2)}(z_{i-1};\boldsymbol{\phi})\right] \tag{14}$$

where $F(y;\phi)$ is the distribution function for y. $F^{(1)}(y;\phi)$ is the first moment distribution function and it is defined as

$$F^{(1)}(y;\phi)=\frac{1}{\mu}\int_0^y t\,f(t;\phi)dt \tag{15}$$

$F^{(2)}(y;\phi)$ is the second moment distribution function and it is defined as

$$F^{(2)}(y;\phi)=\frac{1}{\mu^{(2)}}\int_0^y t^2 f(t;\phi)dt \tag{16}$$

where $\mu=E(y)$ and $\mu^{(2)}=E(y^2)$.

In the study that follows, we assume that income distribution for each country and for a particular year follows a mixture of lognormal distributions. The general form for a mixture density and distribution with J components can be written as

$$f(y;\phi)=\sum_{j=1}^{J} w_j f_j(y;\phi) \qquad \text{and} \qquad F(y;\phi)=\sum_{j=1}^{J} w_j F_j(y;\phi)$$

where w_j is the unknown weight for the component j that needs to be estimated along with the parameters of the distribution. That is $\phi'=(\phi_1',\phi_2',\ldots,\phi_J',w_1,w_2,\ldots,w_{J-1})$. When using mixture density, $k_i(\theta)$ and $m_i^{(\ell)}(\theta)$ are defined as

$$k_i(\theta)=\sum_{j=1}^{J} w_j\left(F_j(z_i;\phi_j)-F_j(z_{i-1};\phi_j)\right)$$

$$m_i^{(\ell)}(\theta)=\sum_{j=1}^{J} w_j\mu_j^{(\ell)}\left(F_j^{(\ell)}(z_i;\phi_j)-F_j^{(\ell)}(z_{i-1};\phi_j)\right) \qquad \ell=1,2$$

For the lognormal components, the forms for $f_j(y;\phi)$, $F_j(y;\phi)$, $\mu_j^{(\ell)}$, and $F_j^{(\ell)}(y;\phi)$ are:

$$f_j(y;\phi_j)=\frac{1}{y\sqrt{2\pi}\sigma_j}\exp\left(-\frac{(\ln y-\beta_j)^2}{2\sigma_j^2}\right) \tag{17}$$

$$F_j(y;\phi_j)=\Phi\left(\frac{\ln(y)-\beta_j}{\sigma_j}\right) \tag{18}$$

$$\mu_j^{(\ell)}=\exp\left(\ell\beta_j+\frac{\ell^2\sigma_j^2}{2}\right) \tag{19}$$

and $$F_j^{(\ell)}\left(y;\phi_j\right) = \Phi\left(\frac{\ln(y) - \beta_j - \ell\sigma_j^2}{\sigma_j}\right) \tag{20}$$

where β_j and σ_j^2 are parameters of the jth component of the mixture of lognormal distribution. Two- and three- component lognormal mixtures are estimated for all the income distributions of the countries and years where we have the data. We have found that the parameters of mixtures with more than 3 components were not estimated accurately and convergence can be difficult. The choice between 2 and 3 components was based on reliability of estimates as judged by their standard errors and the values of J statistics used to test the validity of the moment conditions.

3. Interpolation and Extrapolation

We use interpolation when data are not available in the intervening years between surveys; for years before the earliest year and after the latest year for which survey data are available, we use an extrapolation method. To introduce these methods we need an extra subscript t to specify the time period. For example, for a given country of interest,

$c_{t,i}$ = population share for the *i*-th group in the *t*-th year,

$s_{t,i}$ = income share for the *i*-th group in the *t*-th year,

Suppose data on $c_{t,i}$ and $s_{t,i}$ are available for years $t = 0$ and $t = m$, but are not available for the intervening years $t = 1, 2, \ldots, m-1$. To illustrate the interpolation problem, consider the example a country depicted in Figure 1. Suppose the data on $c_{t,i}$ and $s_{t,i}$ are available for years 1999 and 2004, but not available in any other years. The interpolation problem is to estimate distributions for the years 2000, 2001, 2002 and 2003. The extrapolation problem, which we consider in the next section, is to estimate distributions for 1997, 1998, 2005 and 2006.

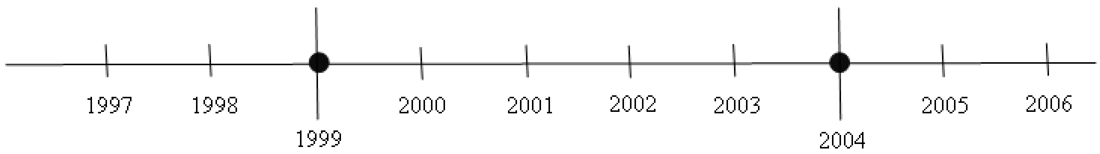

Figure 1: Interpolation and Extrapolation

To describe our method for interpolating the income shares, first suppose $c_{0,i} = c_{m,i}$ for all i. For example, $c_{0,i} = c_{m,i} = 0.1$ for decile shares, although what is critical at this point is that $c_{0,i} = c_{m,i}$ for each *i*; the proportions in each group can be different. For example, the first group may have five percent of the population whereas the second group may have 10 percent of the population and so on. We assume that the change in the income shares for each income class for the intervention years is proportional to the total change in the income shares for the same income class between years $t = 0$ and $t = m$. Interpolation is carried out by interpolating the income shares as follows:

$$s_{t,i} = s_{0,i} + \left(\frac{t-0}{m-0}\right)\left(s_{m,i} - s_{0,i}\right) \tag{21}$$

It can be see that the right hand side is a weighted average of the observed shares in period 0 and *m*. Further, to be able to proceed with GMM estimation of the mixture of lognormal distributions suggested by Griffiths and Hajargasht (2012), we set up the data on class means $\bar{y}_{t,i}$ and the quantity $\tilde{y}_{t,i}$ where $\bar{y}_{t,i} = \dfrac{s_{t,i}\bar{y}_t}{c_{t,i}}$ and $\tilde{y}_i = c_{t,i}\bar{y}_{t,i}$, where $\bar{y}_t$ is the country total mean income for the year *t*. Then these $\tilde{y}_{t,i}$ are used along with proportions $c_{t,i}$ to find GMM-estimated lognormal mixture distributions for the years $t = 1, 2, \ldots, m-1$.

The above method for calculating the $s_{t,i}$ assumes $c_{0,i} = c_{m,i}$. If this equality does not hold we must find a new set of population proportions $c^*_{m,i}$ such that $c^*_{m,i} = c_{o,i}$, and then find income shares $s^*_{m,i}$ that correspond to the population proportions $c^*_{m,i}$. To do this we would need to invert the estimated distribution function at year *m* to find corresponding quantiles, and then find income shares for these quantiles using the first moment distribution function specified in equation (15). The values of $s^*_{m,i}$ are used to replace $s_{m,i}$ in equation (21).

For *extrapolation* of income distributions we use information from countries with similar income distributions. To introduce the approach consider the four countries illustrated in Figure 2. These example scenarios do not exhaust all possible cases, but they are sufficient to describe the main issues. Suppose we are interested in estimating income distributions for countries *A*, *B*, *C* and *D* for the five years from 2000 to 2004, inclusive. The availability of data on $c_{t,i}$ and $s_{t,i}$ is indicated with a black dot. For all other country-year combinations only $\bar{y}_t$ are available.

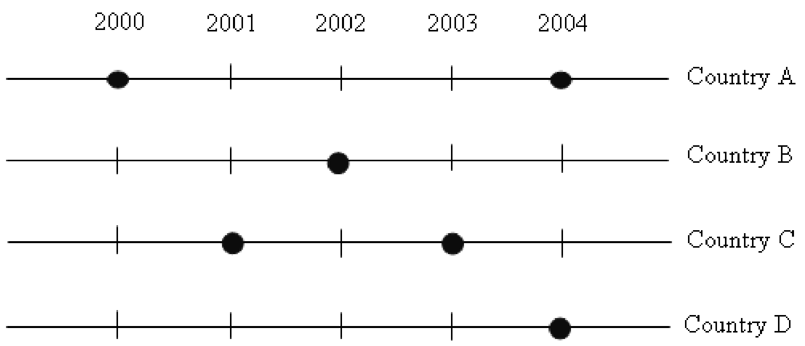

Figure 2: Examples of where extrapolation is required

A general description of how we can proceed follows.

1. Current-price income distributions are estimated for all countries-year combinations where there are black dots.

2. The interpolation method is used to estimate distributions for

   country *A*: 2001, 2002, 2003

   country *C*: 2002

3. We compute weights that reflect the "distance" or "similarity" between the income distributions (*A*, 2002) and (*B*, 2002) and between distributions (*C*, 2002) and (*B*, 2002). Possible distance/similarity measures are described below.

4. For estimating distributions for (*B*, 2001) and (*B*, 2003), we assume that changes in the income shares for these country-year combinations are proportional to a weighted average of the proportional changes observed for countries *A* and *C*. The change is measured relative to 2002 where estimated distributions are available for all three countries *A*, *B*, *C*. The weights are obtained from step 3. The extrapolated income shares are given by:

$$ {}_{j}s_{t+1,i} = {}_{j}s_{t,i} + \sum_{k=1}^{M_0} w_{j,k} \left({}_{k}s_{t+1,i} - {}_{k}s_{t,i} \right) \tag{22} $$

   where subscript j refers to the country of interest. Countries $k = 1, 2, \ldots, M_0$ are those whose income shares are known, either because the original data are available or because they have been interpolated. Further, the corresponding class mean income is obtained from

$$ {}_{j}\overline{y}_{t+1,i} = \frac{{}_{j}s_{t+1,i}}{c_{t,i}} \, {}_{j}\overline{y}_{t+1} \tag{23} $$

5. To obtain distributions for (*C*, 2000) and (*C*, 2004) we follow the same procedure as that in step 4, but we use only the proportional changes in *A* from 2003 to 2004 and from 2001 to 2000. No information is available from other countries.

6. Repeat step 4 to obtain distributions for (*B*, 2000) and (*B*, 2004). Note that information from (*C*, 2000) and (*C*, 2004), obtained in step 5, can be used in this process.

7. Obtain distributions for (*D*, 2000), (*D*, 2001), (*D*, 2002), and (*D*, 2003) using income shares obtained as weighted averages of proportional changes for countries *A*, *B* and *C*.

8. The results from the above procedure will not be invariant with respect to the order in which the countries are considered. For example, instead of finding (*C*, 2000) and (*C*, 2004) before (*B*, 2000) and (*B*, 2004), we could have reversed this order, using information from only *A* to find (*B*, 2000) and (*B*, 2004) and then using information from *A* and *B* to find (*C*, 2000) and (*C*, 2004). To overcome this problem we can use an iterative scheme where information from all available sources is used. Iterating until convergence is likely to be too demanding, but one or two iterations is likely to improve the consistency of the results. A matrix equation involving all countries where extrapolation is required can be set up to compute these iterations.

The missing piece from the above steps is how to measure the distance or similarity between two distributions. To do so, we use a normalized version of Kullback-Leibler (KL) distance (Kullback and Leibler, 1951). Let $f_A(y/\mu_A)$ and $f_B(y/\mu_B)$ be normalized income distributions for countries *A* and *B*, respectively in a given year. Then, the KL divergence of f_B from f_A is

$$KL(A\|B) = \int_0^\infty \ln\left(\frac{f_A(y/\mu_A)}{f_B(y/\mu_B)}\right) f_A(y/\mu_A)\, d(y/\mu_A)$$

As a symmetric measure of distance from *A* to *B* we use

$$D_{A,B} = \frac{1}{2}\left(KL(A\|B) + KL(B\|A)\right)$$

when $f_A(y/\mu_A) = f_B(y/\mu_B)$, $D_{A,B} = 0$. Suppose, we consider the distances of country *A* from a number of other countries $j = 1, 2, \ldots, J$. Then, for weights which reflect the closeness of *A* to each of these countries, we use $w_{A,j} = D_{A,j}^{-1} \Big/ \sum_{l=1}^{J} D_{A,l}^{-1}$. To compute $D_{A,j}^{-1}$ we need to take expectations of the log of mixtures of lognormal distributions, which we do numerically.

4. Combining Country level Distributions

Once distributions have been estimated for every country/year combination, we can find the regional distribution for Africa as a population-weighted mixture of the country-level distributions as described by Chotikapanich et al (2007). Since the country-level distributions are estimated as lognormal mixtures, the regional distributions are essentially mixtures of mixtures.

The density function for the income distribution of a region is given by the mixture $f(y) = \sum_{k=1}^{K} \lambda_k f_k(y)$ where $\lambda_1, \lambda_2, \ldots \lambda_K$ are the population proportions for each country.

The regional cdf is given by $F(y) = \sum_{k=1}^{K} \lambda_k F_k(y)$ and the regional mean income is given by $\mu = \sum_{k=1}^{K} \lambda_k \mu_k$.

5. Measures of Inequality and Poverty for Mixtures of Lognormal distributions

The main purpose of compiling a panel of income distributions is to assess welfare changes over time using various definitions of welfare that take into account inequality, poverty, mean income, and whether growth has favoured the poor. Various measures for these concepts have appeared in the literature, and typically depend on characteristics of the income distribution. To compute values of these measures we express them in terms of the parameters of a mixture of lognormal distributions. Inequality measures that will be considered include the Gini coefficient (*G*), and Theil's measure (*T*)[3]. The expressions for these measures in terms of the parameters of the mixture of lognormal distributions are:

$$G = \frac{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \left\{ \exp\left(\beta_i + 0.5\sigma_i^2\right) \Phi\left(\frac{\sigma_i^2 + \beta_i - \beta_j}{\sqrt{\sigma_i^2 + \sigma_j^2}} \right) \right\}}{\sum_{j=1}^{n} w_j \exp\left(\beta_j + 0.5\sigma_j^2\right)} - 1 \tag{24}$$

and,

$$T = \ln\left(\sum_{j=1}^{n} w_j \exp\left(\beta_j + 0.5\sigma_j^2\right) \right) - \sum_{j=1}^{n} w_j \beta_j \tag{25}$$

where $\left\{\left(\beta_j, \sigma_j^2\right), j = 1, 2, \ldots, n\right\}$ are the parameters of the lognormal mixture.

Poverty measures include the head-count ratio, the poverty gap ratio, the Foster-Greer-Thorbecke index (FGT) and the Watts index[4]. The expressions for these measures in terms of the parameters of the lognormal mixture are given below.

The headcount ratio which gives the proportion of population whose income is below the poverty line, z is given by

[3] Details of these inequality measures and expressions for them in terms of parameters of different distributions that are not mixtures can be found in, for example, Kleiber and Kotz (2003), Jenkins (2009) and McDonald and Ransom (2008).

[4] See Kakwani (1999) for review of various poverty measures and Chotikapanich et al (2013) for their expressions in terms of parameters of a generalized beta distribution.

$$F(z)=\sum_{i=1}^{n} w_i \Phi\left(\frac{\ln(z)-\beta_i}{\sigma_i}\right) \tag{26}$$

The FGT with the inequality aversion $\alpha = 2$ is given by:

$$\begin{aligned} FGT(2) &= \sum_{i=1}^{n} w_i \Phi\left(\frac{\ln(z)-\beta_i}{\sigma_i}\right) - \frac{2}{z}\sum_{i=1}^{n} w_i \exp\left(\beta_i + 0.5\sigma_i^2\right)\Phi\left(\frac{\ln(z)-\beta_i-\sigma_i^2}{\sigma_i}\right) \\ &+ \frac{1}{z^2}\sum_{i=1}^{n} w_i \exp\left(2\beta_i + 2\sigma_i^2\right)\Phi\left(\frac{\ln(z)-\beta_i-2\sigma_i^2}{\sigma_i}\right) \end{aligned} \tag{27}$$

The Watts index is:

$$W=\sum_{j=1}^{n} w_j \sigma_j \left[\left(\frac{\ln z-\beta_j}{\sigma_j}\right)\Phi\left(\frac{\ln z-\beta_j}{\sigma_j}\right)+\phi\left(\frac{\ln z-\beta_j}{\sigma_j}\right)\right] \tag{28}$$

where $\Phi(.)$ is the standard normal cumulative distribution function and $\phi(.)$ is the standard normal probability distribution.

6. Description of Data, Sources and Country Coverage

Two types of data are needed for estimating income distributions: per capita real incomes ($\bar{y}$) made comparable over time and countries using purchasing power parity (PPP) exchange rates, and data on the distribution of income within each country. For per capita real incomes ($\bar{y}$) expressed in PPP dollars we obtain the data from the Penn World Table 8.0 (PWT8.0) that covers 180 countries annually from 1950 to 2010. PWT8.0 also provides data on the population size of each country, needed for finding regional distributions. The real income variable denoted by *cgdpe*[5], that we use to calculate per capita real income ($\bar{y}$) for each country, expressed in current prices, has been adjusted for differences in prices across countries.

We use income distribution data from the PovcalNet website developed by the World Bank poverty research group. This database is set up for the purpose of poverty assessment for individual countries, regions and globally. The data are provided in grouped form and can be downloaded from http://iresearch.worldbank.org/PovcalNet/index.htm. For each country, the reported data are in the form of cumulative proportion of population and income or expenditure from which we can calculate population shares (c_i) and expenditure/income shares (s_i). Most of the data are available as 20 income/expenditure share groups. Throughout the paper we use the generic term *income distributions* although almost all of our data are for expenditure.

[5] The term *cgdpe* is an acronym used by PWT for real GDP per capita constructed using current prices.

Regarding the data coverage, we began with as many countries in Africa as possible where we have the data on both per capita real incomes and the corresponding income distributions. Our data set include 40 countries with the data scatter between 1993 and 2011. These countries are mostly in Sub-Saharan Africa and they cover most of the countries in the Sub-Saharan Africa. For each country, the number of years where the data are available range between 1 and 5 years. These countries and the years where the data are available are listed in Table 1.

(Table 1 here)

7. Empirical Results

The main objective of the paper is to compile a panel of income distributions for 40 Sub-Saharan African countries and for the period 1993 to 2011. As a first step in this process, we first fit mixture of lognormal distributions using GMM discussed in Section 2. Considering the limitations of space, we focus our presentation to a subset of ten countries. These are: Central African Republic; Ethiopia; Ghana; Kenya; Mozambique; Nigeria; Senegal; Sierra Leone; South Africa and Tanzania.

Table 2 presents the estimated parameters of the mixtures of lognormal distributions for the 10 countries. For example, consider the fitted distribution for Ethiopia in 1997 from Table 2. Column 2 indicates whether the estimates were obtained from observed data (O), interpolated data (I) or extrapolated data (E).; Column 3 indicates the form of the best fitting distribution and the remaining columns show the estimated parameters. In the case of Ethiopia, the best fitting distribution is a mixture of two lognormal distributions with both variances estimates which is indicated by (2,2).[6] In the case of Ethiopia, noting that for a random variable $X \sim LN(\mu, \sigma^2) \Leftrightarrow \ln X \sim N(\mu, \sigma^2)$ where *LN* and *N* denote lognormal and normal distributions, the parameters estimated for Ethiopia are:

μ_1 =5.759; σ_1 = 0.0468; weight$_1$ = 0.904 and μ_2 =6.575; σ_2 = 0.871; weight$_2$ = 0.096

This means that the first distribution has 90% weight compared to 10% for the second distribution and hence the first distribution is the main driver of the distribution.

(Table 2: Fitted Distributions for 10 African countries and for Selected Years)

A feature worth noting in Table is the stability of the fitted distributions over time. There are no major shifts in the number of distributions involved in the mixture nor are there major changes in the weights accorded to the distributions in the mixture. This stability is an encouraging feature which provides a basis for interpolation and extrapolation of distributions based on the observed distributions.

[6] If the column shows (3,2) then it means that the fitted distribution is a mixture of three lognormal distributions but only two variances are estimated. This means that the last two components of the mixture have the same variance parameter.

The following figures show the estimated densities for the years 1997, 2004 and 2010 for Ethiopia, Nigeria and Sierra Leone.

(insert Figure 1 here)

Fitted distributions for Nigeria and Sierra Leone are consistent with expectations showing a rightward shift in the distributions. In the case of Nigeria, the profile of distributions suggests a strong growth in real per capita income and also a significant reduction in inequality. The case of Ethiopia is somewhat puzzling as the distribution in 2004 shifted to the left of the distribution in 1997 indicating a significant drop in real per capita income and then an expected rightward shift in the distribution for 2010. This could be partly driven by the data on real per capita income from the Penn World Tables (PWT 8.0). From Table 9, it can be seen that real per capita income in constant 2005 prices has dropped from $448.32 in 1997 to $287.18 in 2004. This drop in mean income implies a shift of the distribution in 2004 to the left of the distribution in 1997.

Interpolation and extrapolation of income distribution data

Table 3 shows the current availability of data for the ten countries under consideration. All the entries coloured in *yellow* shows the current availability of income distribution data. Income distribution data are indeed sparse with only 21 entries out of possible 240 (10 countries by 14 years) in yellow showing availability. This means that we need to interpolate or extrapolate using data available. As discussed in Section 3, income distributions are interpolated for all the years in between the years when data are available, i.e., for all the years between yellow coloured squares (these are the squares in *green*). We need to extrapolate the distributions for all the *light organge* coloured squares. There are 21 entries (countries and years) for which extrapolations are made. Our methodology for interpolation is quite simple as it interpolates the income shares for the decile or quintile groups but extrapolation requires the computation of Kullback-Leibler measures of distance[7] between pairs of income distributions. The weights implied are presented in Table 4.

(Table 4 here)

The table shows the years for which extrapolations are made and the weights attached to the distributions from different countries. For example, consider the first row of the table. This corresponds to the extrapolation of income distribution for Central African Republic in 2009. This distribution is derived as a weighted average of the distributions from Ethiopia, Ghana, Kenya, Mozambique, Nigeria, Senegal, Sierra Leone, South Africa and Tanzania. Of these countries, the biggest weight of 0.22 is for the distribution of Sierra Leone followed by Ghana with a weight of 0.166 and Kenya with a weight of 0.147. The lowest weight is given to the distribution from Ethiopia.

[7] The matrix of Kullback-Leibler distances is computed for all the 40 countries in the study but only relevant parts of the distance matrix are used in this paper.

These weights suggest that the usual *naïve* approach of using the distribution of the geographically closest neighbour may not be the best approach to be used.

Using the procedures described in Section 3, we compile the full set of 240 income distribution based on the observed, interpolated or extrapolated income distributions. These distributions are used in assessing the inequality and poverty situation in the selected 10 African countries over the period 1997 to 2010.

Inequality and poverty

In tables 5 and 6 we present the estimated Gini and Theil's measures of inequalities for the 10 selected countries. Tables 7 and 8 present the head count ratio and Foster-Greer-Thorbecke index with parameter value of 2 (FGT(2)).

We observe increase in inequality over the period 1997 to 2010 in Central African Republic, Ghana, Kenya, South Africa and Tanzania whereas marginal decrease in inequality is observed in other countries of the region. Of particular relevance is the increase in inequality in South Africa, Ghana and Kenya. The time profiles of inequality measures are shown in Figure 2 for Nigeria, Ethiopia and Sierra Leone.

However, no such simple profile can be observed for poverty measures. As poverty measures are determined by real per capita income as well as inequality in the distribution of income, we observe significant fluctuations in head count ratio as well as FGT (2) for Nigeria, Ethiopia and Sierra Leone. These fluctuations can be largely attributable to fluctuations in real per capita income shown in Table 9.

8. Conclusions

We have shown how estimation, interpolation and extrapolation can be used to construct a panel of income distributions for a subset of African countries. This panel can be used to analyse changes in poverty, inequality and other measures of interest. The paper is part of a larger study which will eventually include many more countries.

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Table 1: Country coverage

Country	Years where there are data available
Angola	2000, 2008
Benin	2003
Burnika Faso	1994, 1998, 2003, 2009
Burundi	1998, 2006
Cameroon	1996, 2001, 2007
Cape Verda	2001
Central African Republic	1992, 2003, 2008
Chad	2002
Comoros	2004
Congo, Dem Rep.	2005
Congo, rep.	2005
Cote D'Ivoire	1995, 1998, 2002, 2005, 2008
Ethiopia	1995, 1999, 2005, 2010
Gabon	2005
Gambia	1998, 2003,
Ghana	1991, 1998, 2003, 2005
Guinea	1994, 2003
Guinea Bissua	1993, 2002
Kenya	1994, 1997, 2002, 2005
Lesotho	1994, 2002
Liberia	2007
Madagascar	1997, 1999, 2001, 2005, 2010
Malawi	1997, 2004, 2010
Mali	1994, 2001, 2006, 2010
Mauritania	1995, 2000, 2004, 2008
Mozambique	1996, 2002, 2007
Namibia	1993, 2003
Niger	1994, 2005, 2007
Nigeria	1996, 2003, 2009, 2011
Rwanda	2000, 2005, 2010
Sao Tome and Principe	2000
Senegal	1994, 2001, 2005, 2011
Siera Leone	2003, 2011
South Africa	1995, 2001, 2005, 2008
Sudan	2009
Swaziland	1994, 2000, 2009
Tanzania	1991, 2000, 2007
Togo	2006, 2011

Uganda	1996, 1999, 2002, 2005, 2009
Zambia	1996, 1998, 2002, 2004, 2006, 2010

Source: PovalNet as of June, 2014 at http://iresearch.worldbank.org/PovcalNet/index.htm

Table 2: Fitted Distributions for 10 Selected African Countries, 1997, 2004, 2010

Country	Year	Data	Model	mu1	sig1	w1	mu2	sig2	w2	mu3	sig3	w3
Central African Republic	1997	I	3,2	5.4572	0.8121	0.8290	6.5477	0.3101	0.1011	7.7046	0.3101	0.0699
Central African Republic	1998	I	3,2	5.5480	0.7780	0.8258	6.5776	0.2964	0.1005	7.6999	0.2964	0.0737
Central African Republic	1999	I	3,2	5.5305	0.7498	0.8260	6.4983	0.2790	0.0974	7.5890	0.2790	0.0766
Central African Republic	2000	I	3,2	5.6105	0.7269	0.8307	6.5136	0.2540	0.0906	7.5760	0.2540	0.0787
Central African Republic	2001	I	3,2	5.6868	0.7061	0.8337	6.5333	0.2424	0.0874	7.5676	0.2424	0.0789
Central African Republic	2002	I	3,2	5.7122	0.6941	0.8523	6.4851	0.1907	0.0702	7.4995	0.1907	0.0776
Central African Republic	2003	O	3,2	5.3011	0.5584	0.4364	6.1556	0.5423	0.4914	7.2166	0.5423	0.0722
Central African Republic	2004	I	3,2	4.8313	0.2249	0.0254	5.8409	0.7412	0.9264	7.3281	0.7412	0.0482
Central African Republic	2005	I	3,2	4.7579	0.2135	0.0217	5.8205	0.7705	0.9420	7.6301	0.7705	0.0362
Central African Republic	2006	I	3,2	4.6659	0.2088	0.0181	5.7768	0.8007	0.9507	7.8383	0.8007	0.0313
Central African Republic	2007	I	3,2	4.5821	0.2047	0.0139	5.7420	0.8351	0.9582	8.0265	0.8351	0.0278
Central African Republic	2008	O	3,2	4.3996	0.5002	0.0580	5.7872	0.8000	0.9010	8.0063	0.8000	0.0410
Central African Republic	2009	E	2,2	5.6502	0.8692	0.9295	6.9368	1.3174	0.0705			
Central African Republic	2010	E	2,2	5.7373	0.7706	0.8597	6.2770	1.3980	0.1403			
Ethiopia	1997	I	2,2	5.7595	0.4680	0.9036	6.5754	0.8708	0.0964			
Ethiopia	1998	I	2,2	5.6459	0.4400	0.8778	6.2434	0.8376	0.1222			
Ethiopia	1999	O	2,2	5.6596	0.4117	0.8407	6.0778	0.7728	0.1593			
Ethiopia	2000	I	2,2	5.5603	0.4153	0.8631	6.0505	0.7690	0.1369			
Ethiopia	2001	I	2,2	5.5723	0.4185	0.8846	6.1551	0.7587	0.1154			
Ethiopia	2002	I	2,2	5.5581	0.4235	0.9210	6.3943	0.6937	0.0790			
Ethiopia	2003	I	3,2	5.0846	0.1190	0.0309	5.4842	0.4322	0.9345	6.8920	0.4322	0.0346
Ethiopia	2004	I	3,2	5.2714	0.3517	0.5861	5.7737	0.3142	0.3713	6.8888	0.3142	0.0426
Ethiopia	2005	O	3,2	5.4353	0.3314	0.5225	5.9552	0.3093	0.4333	7.0886	0.3093	0.0442
Ethiopia	2006	I	2,2	5.7730	0.4339	0.9386	6.8150	0.6409	0.0614			
Ethiopia	2007	I	2,2	5.8726	0.4427	0.8901	6.4960	0.7873	0.1099			
Ethiopia	2008	I	3,1	5.4673	0.4410	0.0801	6.0242	0.4410	0.8739	7.3512	0.4410	0.0460
Ethiopia	2009	I	3,1	5.4834	0.4378	0.0870	6.1690	0.4378	0.8610	7.4610	0.4378	0.0519
Ethiopia	2010	O	3,1	5.4142	0.4424	0.0749	6.2554	0.4424	0.8689	7.5364	0.4424	0.0561
Ghana	1997	I	3,2	6.6785	0.6732	0.8893	7.5116	0.2780	0.0779	8.3808	0.2780	0.0329
Ghana	1998	O	3,2	6.6619	0.6855	0.8812	7.5172	0.2746	0.0858	8.3663	0.2746	0.0329
Ghana	1999	I	3,2	6.8889	0.7077	0.9156	7.7049	0.2629	0.0588	8.6221	0.2629	0.0256
Ghana	2000	I	3,2	6.7463	0.7450	0.9782	7.3743	0.1106	0.0134	8.6570	0.1106	0.0084
Ghana	2001	I	3,1	6.1337	0.6863	0.1954	6.7733	0.6863	0.7740	7.9283	0.6863	0.0306
Ghana	2002	I	3,1	6.0752	0.6595	0.1436	6.8882	0.6595	0.8072	8.0389	0.6595	0.0492
Ghana	2003	I	3,1	5.9909	0.6434	0.1258	6.9115	0.6434	0.8177	8.1069	0.6434	0.0564
Ghana	2004	I	3,1	5.9677	0.6307	0.1162	6.9719	0.6307	0.8230	8.2119	0.6307	0.0607
Ghana	2005	O	3,1	5.9422	0.6305	0.1021	7.0294	0.6305	0.8402	8.3355	0.6305	0.0577
Ghana	2006	E	3,1	5.9031	0.6360	0.0991	6.9934	0.6360	0.8427	8.3455	0.6360	0.0582
Ghana	2007	E	3,1	5.8704	0.6495	0.0880	6.9839	0.6495	0.8567	8.3977	0.6495	0.0553
Ghana	2008	E	3,1	5.9233	0.6621	0.0770	7.0593	0.6621	0.8691	8.5379	0.6621	0.0538
Ghana	2009	E	3,1	5.8864	0.6731	0.0653	7.0511	0.6731	0.8809	8.5730	0.6731	0.0538
Ghana	2010	E	3,1	5.7376	0.6536	0.0316	7.2055	0.6536	0.9229	8.6211	0.6536	0.0455
Kenya	1997	O	3,2	6.0093	0.2837	0.1522	6.8883	0.5477	0.7840	8.3353	0.5477	0.0638
Kenya	1998	I	3,2	5.9632	0.3137	0.1431	6.8385	0.5682	0.7955	8.3190	0.5682	0.0615
Kenya	1999	I	3,2	5.9298	0.3570	0.1398	6.7866	0.5899	0.8020	8.3019	0.5899	0.0583
Kenya	2000	I	3,2	5.8803	0.4213	0.1489	6.6927	0.6120	0.7968	8.2420	0.6120	0.0543
Kenya	2001	I	3,1	6.1708	0.5657	0.5108	6.9131	0.5657	0.4442	8.3446	0.5657	0.0450
Kenya	2002	I	2,2	6.4179	0.6695	0.8326	7.1894	0.9728	0.1674			
Kenya	2003	I	2,2	6.3957	0.6488	0.7293	6.8349	1.0468	0.2707			
Kenya	2004	I	2,2	6.4672	0.5764	0.7302	6.5572	1.1704	0.2698			
Kenya	2005	O	3,2	6.2817	1.5518	0.0853	6.2846	0.6351	0.7809	7.3702	0.6351	0.1339
Kenya	2006	E	3,2	6.1212	0.4786	0.4097	6.5768	1.1320	0.3723	6.9148	0.4786	0.2180
Kenya	2007	E	3,2	6.1611	0.4849	0.4250	6.6271	1.1573	0.3575	6.9735	0.4849	0.2175
Kenya	2008	E	3,2	6.1070	0.4935	0.4455	6.5859	1.1850	0.3406	6.9404	0.4935	0.2139
Kenya	2009	E	3,2	6.1428	0.4969	0.4581	6.6384	1.2025	0.3319	6.9946	0.4969	0.2100
Kenya	2010	E	3,2	6.2039	0.4145	0.3932	6.7030	1.1192	0.3652	7.0000	0.4145	0.2416
Mozambique	1997	I	3,2	5.2966	0.2025	0.0513	5.5049	0.6765	0.9073	7.3160	0.6765	0.0413
Mozambique	1998	I	3,2	5.4024	0.3495	0.1298	5.5350	0.7030	0.8326	7.3860	0.7030	0.0376
Mozambique	1999	I	2,2	5.4869	0.5813	0.7609	5.9960	1.0756	0.2391			
Mozambique	2000	I	3,2	5.3818	0.3666	0.1625	5.5040	0.7119	0.8003	7.4269	0.7119	0.0372
Mozambique	2001	I	3,2	5.3401	0.3667	0.1715	5.4600	0.7143	0.7912	7.4175	0.7143	0.0373
Mozambique	2002	O	3,2	5.5728	0.3821	0.1919	5.6910	0.7172	0.7702	7.6745	0.7172	0.0379
Mozambique	2003	I	2,2	5.6446	0.5831	0.7681	6.1169	1.1373	0.2319			
Mozambique	2004	I	2,2	5.7132	0.5920	0.7706	6.1143	1.1593	0.2294			
Mozambique	2005	I	2,2	5.8086	0.6023	0.7785	6.1403	1.1868	0.2215			
Mozambique	2006	I	3,1	0.3571	0.6663	0.0062	5.8551	0.6663	0.9579	7.8299	0.6663	0.0359
Mozambique	2007	O	3,1	0.0736	0.6741	0.0072	5.9045	0.6741	0.9610	7.8972	0.6741	0.0319
Mozambique	2008	E	3,2	5.6443	0.4820	0.3980	6.1683	1.2252	0.2462	6.3485	0.4820	0.3558
Mozambique	2009	E	3,2	5.6721	0.4864	0.4187	6.1993	1.2411	0.2422	6.3818	0.4864	0.3391
Mozambique	2010	E	3,2	5.7268	0.4043	0.3633	6.2461	1.1552	0.2706	6.4454	0.4043	0.3662

Table 2: Fitted Distributions for 10 Selected African Countries, 1997, 2004, 2010 (cont)

Country	Year	Data	Model	mu1	sig1	w1	mu2	sig2	w2	mu3	sig3	w3
Nigeria	1997	I	3,1	3.7720	0.6560	0.0674	4.8095	0.6560	0.8796	6.4628	0.6560	0.0530
Nigeria	1998	I	3,1	3.9084	0.6575	0.0767	4.9238	0.6575	0.8709	6.5177	0.6575	0.0524
Nigeria	1999	I	3,1	3.6689	0.6591	0.0858	4.6680	0.6591	0.8622	6.1973	0.6591	0.0520
Nigeria	2000	I	3,1	3.8254	0.6606	0.0947	4.8127	0.6606	0.8533	6.2699	0.6606	0.0520
Nigeria	2001	I	3,1	4.6363	0.6620	0.1032	5.6157	0.6620	0.8442	6.9904	0.6620	0.0527
Nigeria	2002	I	3,1	4.7746	0.6628	0.1111	5.7494	0.6628	0.8338	7.0256	0.6628	0.0551
Nigeria	2003	O	3,2	4.5683	0.4256	0.0267	6.1127	0.7103	0.9253	7.3119	0.7103	0.0480
Nigeria	2004	I	2,2	6.2905	0.6728	0.5676	6.3610	0.9532	0.4324			
Nigeria	2005	I	2,2	6.6005	0.6996	0.6529	6.7391	0.9997	0.3471			
Nigeria	2006	I	2,2	6.2686	0.7110	0.6749	6.4729	1.0237	0.3251			
Nigeria	2007	I	2,2	6.7491	0.7182	0.6797	7.0162	1.0388	0.3203			
Nigeria	2008	I	2,2	6.4667	0.7235	0.6778	6.7942	1.0494	0.3222			
Nigeria	2009	O	2,2	6.7175	0.7216	0.6552	7.0985	1.0521	0.3448			
Nigeria	2010	I	2,2	6.7162	0.6415	0.5948	6.9099	0.9718	0.4052			
Senegal	1997	I	3,2	6.4090	0.0188	0.0213	6.7861	0.5708	0.8967	8.2230	0.5708	0.0820
Senegal	1998	I	3,2	6.4142	0.0718	0.0245	6.8042	0.5722	0.8951	8.2424	0.5722	0.0804
Senegal	1999	I	3,2	6.3762	0.1363	0.0382	6.7962	0.5795	0.8884	8.2503	0.5795	0.0734
Senegal	2000	I	3,2	6.6186	0.5160	0.8231	7.3785	0.2527	0.0974	8.3636	0.2527	0.0795
Senegal	2001	O	3,2	6.5445	0.4766	0.7413	7.2879	0.2689	0.1674	8.3006	0.2689	0.0914
Senegal	2002	I	3,2	6.3136	0.2114	0.0704	6.7765	0.6322	0.8989	8.4580	0.6322	0.0307
Senegal	2003	I	3,2	0.2262	4.2529	0.0085	6.4947	0.4693	0.6402	7.3727	0.4693	0.3512
Senegal	2004	I	3,2	0.2601	4.1408	0.0114	6.4770	0.4696	0.6105	7.3457	0.4696	0.3781
Senegal	2005	O	3,2	6.5876	1.3423	0.0612	6.5916	0.5456	0.6764	7.3720	0.5456	0.2624
Senegal	2006	I	3,1	0.2628	0.6220	0.0048	6.7413	0.6220	0.9123	7.8332	0.6220	0.0829
Senegal	2007	I	3,1	0.2328	0.6117	0.0054	6.7473	0.6117	0.8905	7.8086	0.6117	0.1041
Senegal	2008	I	3,1	0.2016	0.6028	0.0061	6.7387	0.6028	0.8731	7.7914	0.6028	0.1208
Senegal	2009	I	3,1	0.1770	0.5950	0.0067	6.7653	0.5950	0.8596	7.8206	0.5950	0.1337
Senegal	2010	I	3,1	0.1478	0.5883	0.0073	6.7339	0.5883	0.8492	7.7977	0.5883	0.1435
Sierra Leone	1997	I	2,2	5.5134	0.3470	0.2940	6.8162	0.8335	0.7060			
Sierra Leone	1998	I	3,2	5.4885	0.4232	0.4636	6.6677	0.4468	0.4130	7.7454	0.4468	0.1234
Sierra Leone	1999	I	3,2	5.3507	0.1639	0.1424	5.3568	0.8602	0.0745	6.2362	0.8602	0.7831
Sierra Leone	2000	I	3,2	5.4274	0.1660	0.1085	5.8855	0.7451	0.6355	6.7914	0.7451	0.2560
Sierra Leone	2001	I	3,2	5.6012	0.1700	0.0730	5.9687	0.6614	0.7064	7.0651	0.6614	0.2206
Sierra Leone	2002	I	2,2	5.9953	0.5631	0.7586	7.1649	0.6059	0.2414			
Sierra Leone	2003	O	2,2	6.0452	0.5721	0.8490	7.3457	0.5311	0.1510			
Sierra Leone	2004	I	3,2	6.0226	0.5652	0.8777	7.0846	0.2021	0.0669	7.8420	0.2021	0.0554
Sierra Leone	2005	I	2,2	5.9566	0.5475	0.8516	7.1875	0.5322	0.1484			
Sierra Leone	2006	I	3,2	5.9807	0.5406	0.8810	6.9714	0.1936	0.0638	7.7327	0.1936	0.0552
Sierra Leone	2007	I	2,2	5.9562	0.4116	0.4434	6.4199	0.7557	0.5566			
Sierra Leone	2008	I	3,2	6.0499	0.4113	0.4794	6.0513	0.7190	0.0905	6.6042	0.7190	0.4301
Sierra Leone	2009	I	2,2	6.1250	0.4004	0.4686	6.5456	0.7339	0.5314			
Sierra Leone	2010	I	2,2	6.1913	0.3981	0.4892	6.5907	0.7256	0.5108			
South Africa	1997	I	3,2	7.0217	0.6046	0.4584	7.8660	0.6645	0.3658	9.2132	0.6645	0.1759
South Africa	1998	I	3,2	7.0337	0.6287	0.5186	7.9510	0.6428	0.3097	9.2342	0.6428	0.1717
South Africa	1999	I	3,2	7.0628	0.6548	0.5663	8.0367	0.6237	0.2644	9.2660	0.6237	0.1692
South Africa	2000	I	3,2	7.1149	0.6859	0.6168	8.1510	0.6020	0.2184	9.3189	0.6020	0.1648
South Africa	2001	O	3,2	7.0550	0.6729	0.5708	8.0279	0.6696	0.2641	9.3302	0.6696	0.1651
South Africa	2002	I	3,2	7.0052	0.6689	0.5460	7.9104	0.7299	0.2899	9.3281	0.7299	0.1642
South Africa	2003	I	3,2	7.0332	0.6763	0.6167	8.0681	0.7591	0.2395	9.4352	0.7591	0.1438
South Africa	2004	I	3,2	7.0466	0.6746	0.6521	8.1930	0.7888	0.2188	9.5509	0.7888	0.1290
South Africa	2005	O	3,2	7.0881	0.6763	0.7199	8.5811	0.7230	0.1916	9.9311	0.7230	0.0885
South Africa	2006	I	3,2	6.9892	0.5448	0.2721	7.5434	0.8351	0.5543	9.4979	0.8351	0.1736
South Africa	2007	I	3,2	6.9638	0.4766	0.1746	7.5513	0.8027	0.6400	9.5048	0.8027	0.1854
South Africa	2008	O	3,2	6.9458	0.4243	0.1276	7.5647	0.7822	0.6720	9.4757	0.7822	0.2003
South Africa	2009	E	3,2	6.8842	0.3939	0.1241	7.5393	0.7843	0.6766	9.4797	0.7843	0.1994
South Africa	2010	E	3,2	7.4670	0.6162	0.6904	8.7734	0.5900	0.2053	9.9679	0.5900	0.1043
Tanzania	1997	I	3,2	5.9050	0.1986	0.0813	5.9856	0.6175	0.8935	6.9742	0.6175	0.0251
Tanzania	1998	I	3,2	4.9866	0.3026	0.0526	6.0012	0.4795	0.8241	6.9236	0.4795	0.1234
Tanzania	1999	I	3,2	5.8367	0.0391	0.0248	6.0313	0.5912	0.9349	7.0212	0.5912	0.0403
Tanzania	2000	O	3,2	5.1060	0.4035	0.0645	5.9921	0.4902	0.8218	6.9220	0.4902	0.1137
Tanzania	2001	I	3,2	5.7791	0.0411	0.0230	5.9885	0.5927	0.9351	7.0339	0.5927	0.0419
Tanzania	2002	I	3,2	4.9229	0.3040	0.0351	5.9826	0.5186	0.8691	6.9886	0.5186	0.0957
Tanzania	2003	I	2,2	5.9101	0.5130	0.5817	6.1498	0.7535	0.4183			
Tanzania	2004	I	2,2	5.9289	0.5195	0.6098	6.1757	0.7737	0.3902			
Tanzania	2005	I	2,2	5.9919	0.5254	0.6332	6.2452	0.7938	0.3668			
Tanzania	2006	I	2,2	5.9966	0.5308	0.6522	6.2556	0.8134	0.3478			
Tanzania	2007	O	2,2	6.0055	0.5345	0.6624	6.2629	0.8329	0.3376			
Tanzania	2008	E	2,2	6.0304	0.5395	0.6931	6.3420	0.8574	0.3069			
Tanzania	2009	E	2,2	6.0469	0.5392	0.6999	6.3968	0.8693	0.3001			
Tanzania	2010	E	2,2	6.1809	0.5006	0.6438	6.3581	0.8028	0.3562			

Figure 1: Plots of estimated densities over time

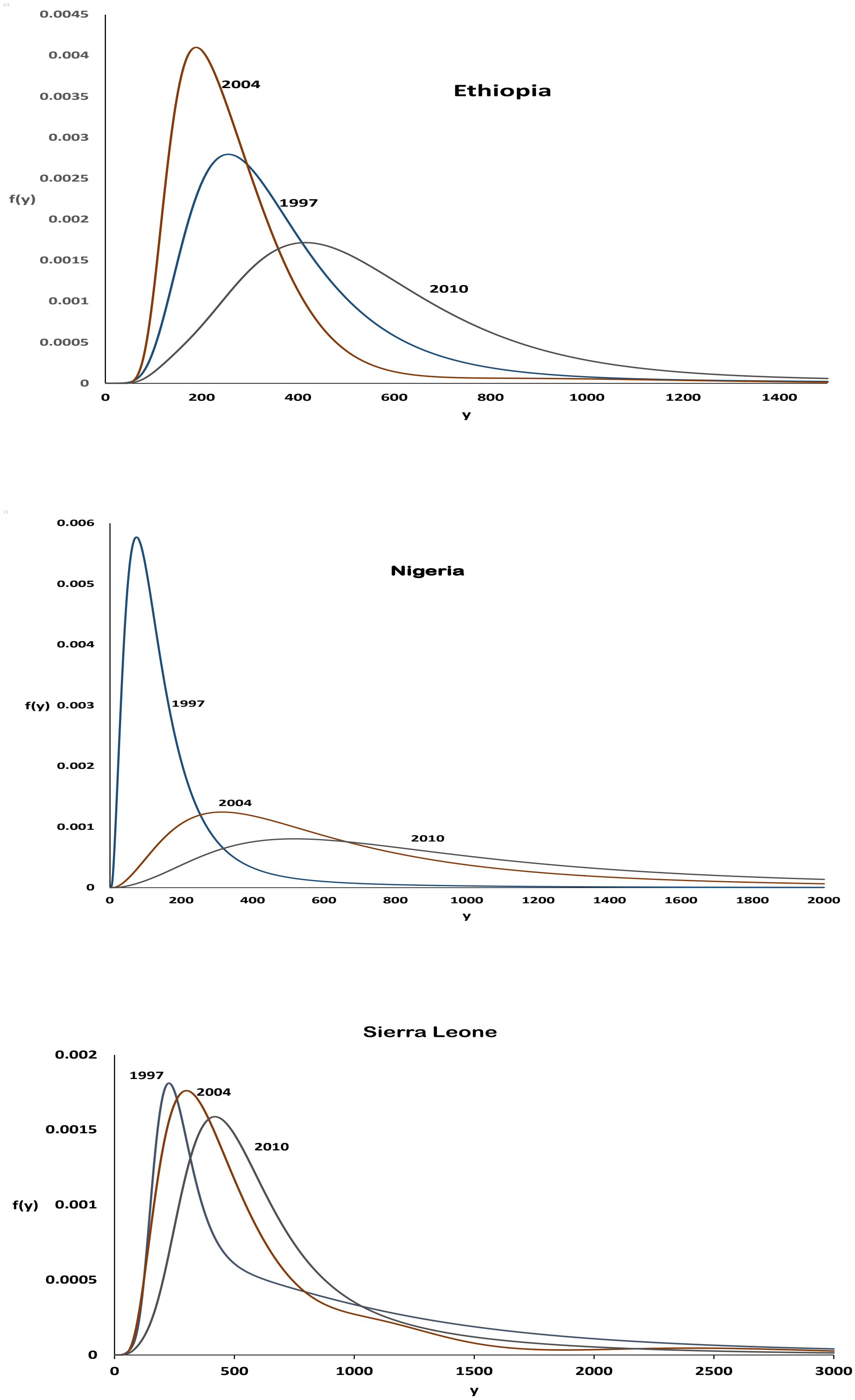

Figure 2: Plots of Gini over time

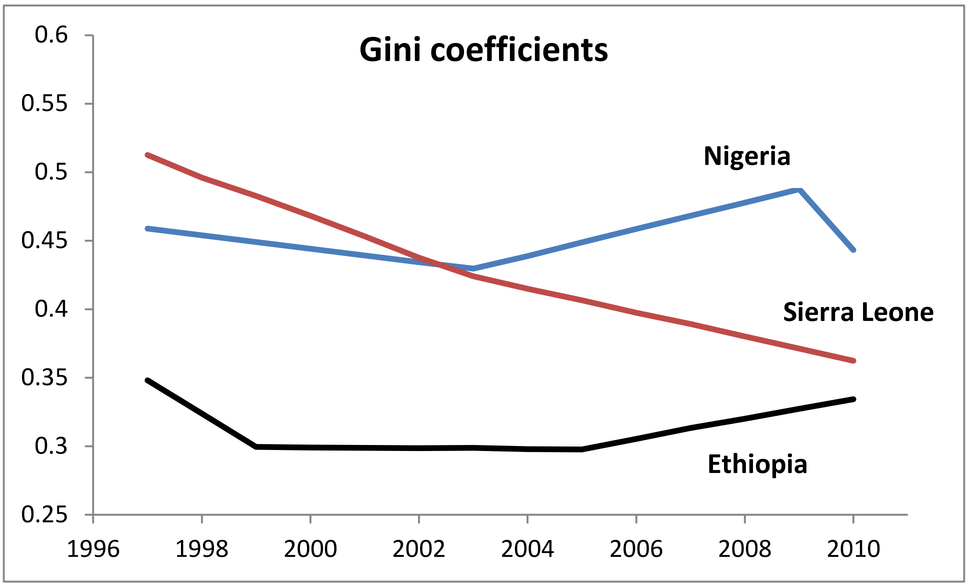

Figure 3:Plot of head count ratios.

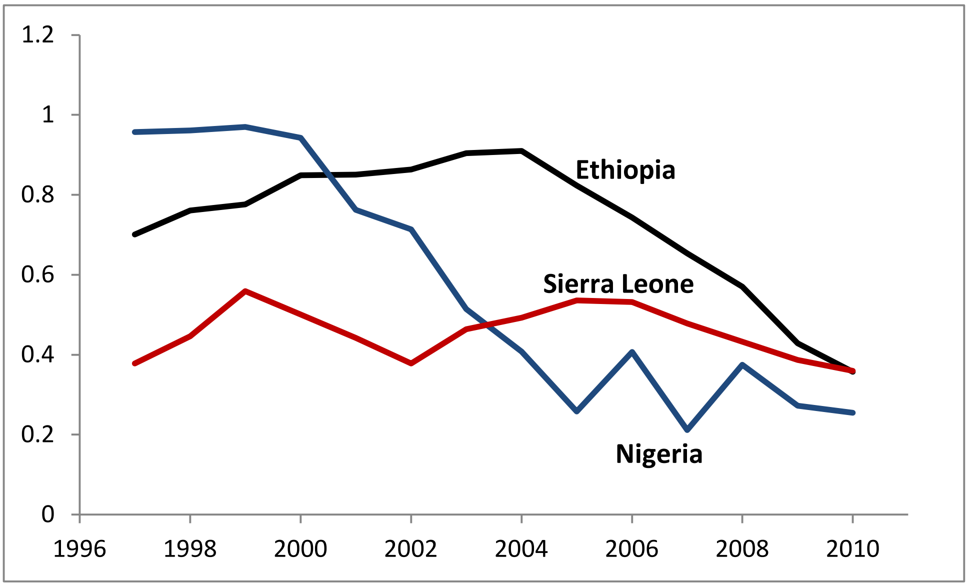

Figure 4: Plot of FGT2

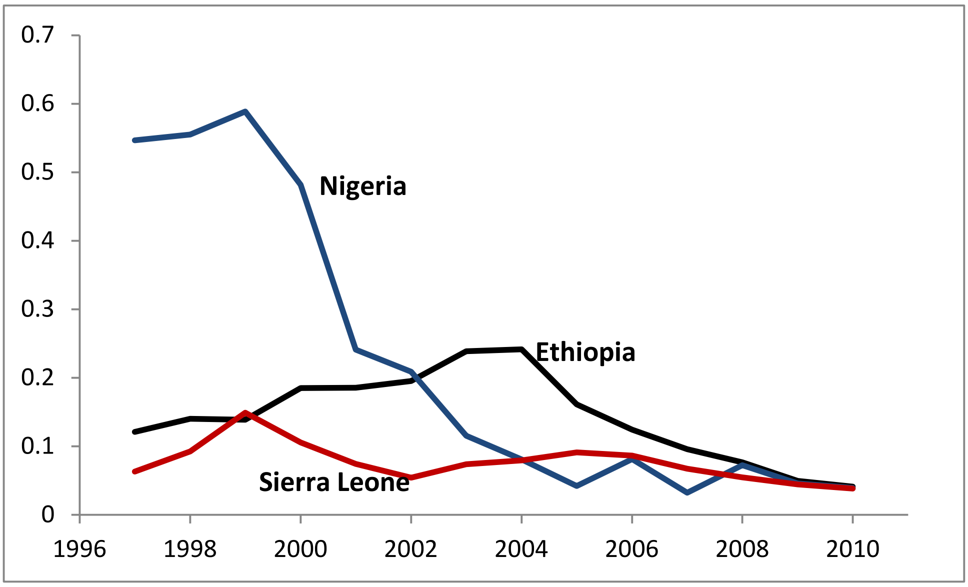

Table 3: Years where interpolation are done and years where extrapolation are done – Selected countries, 1997-2010

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Central African Republic														
Ethiopia														
Ghana														
Kenya														
Mozambique														
Nigeria														
Senegal														
Siera Leone														
South Africa														
Tanzania														

Note: Meanings of colours.

	The years where there are data
	The years where interpolation is done
	The years where extrapolation is done

Table 4: Weights used for extrapolation.

	Extrapolated years	Central Africa Rep	Ethiopia	Ghana	Kenya	Mozambique	Nigeria	Senegal	Sierra Leone	South Africa	Tanzania
Central Africa	2009		0.0168	0.1658	0.1469	0.0982	0.1912	0.0746	0.2201	0.0417	0.0448
	2010		0.0334				0.3804	0.1485	0.4378		
Ghana	2006	0.06110	0.0105			0.0896	0.6270	0.0329	0.1224	0.0103	0.0463
	2007	0.06110	0.0105			0.0896	0.6270	0.0329	0.1224	0.0103	0.0463
	2008	0.07071	0.0121				0.7256	0.0380	0.1416	0.0119	
	2009		0.0132				0.7910	0.0414	0.1544		
	2010	0.07156	0.0123				0.7344	0.0385	0.1433		
Kenya	2006	0.05226	0.0093	0.1805		0.3011	0.2122	0.0344	0.1666	0.0100	0.0337
	2007	0.05226	0.0093	0.1805		0.3011	0.2122	0.0344	0.1666	0.0100	0.0337
	2008	0.07856	0.0140	0.2714			0.3190	0.0517	0.2504	0.0150	
	2009		0.0154	0.2994			0.3519	0.0570	0.2763		
	2010	0.07975	0.0142	0.2755			0.3238	0.0524	0.2543		
Mozambique	2008	0.05177	0.0140	0.1282	0.4464		0.1821	0.0387	0.1240	0.0147	
	2009		0.0150	0.1373	0.4782		0.1951	0.0415	0.1328		
	2010	0.05255	0.0143	0.1301	0.4531		0.1849	0.0393	0.1259		
South Africa	2009		0.0378	0.1628	0.1634	0.1631	0.2021	0.0754	0.1954		
	2010	0.19561	0.0304	0.1310	0.1315	0.1312	0.1626	0.0606	0.1572		
Tanzania	2008	0.06185	0.1307	0.1737	0.1309	0.1128	0.1198	0.1623	0.0912	0.0167	
	2009		0.1393	0.1852	0.1396	0.1202	0.1277	0.1730	0.0972	0.0178	
	2010	0.06185	0.1307	0.1737	0.1309	0.1128	0.1198	0.1623	0.0912	0.0167	

Table 5: Gini coefficients for the 10 selected countries, 1997-2010

	Central Africa Rep	Ethiopia	Ghana	Kenya	Mozambique	Nigeria	Senegal	Sierra Leone	South Africa	Tanzania
1997	0.5298	0.3482	0.4039	0.4234	0.4495	0.4588	0.4115	0.5126	0.5696	0.3433
1998	0.5134	0.3239	0.4078	0.4301	0.4530	0.4539	0.4112	0.4959	0.5721	0.3438
1999	0.4971	0.2996	0.4105	0.4368	0.4564	0.4490	0.4113	0.4827	0.5745	0.3459
2000	0.4808	0.2992	0.4126	0.4435	0.4614	0.4441	0.4085	0.4682	0.5770	0.3460
2001	0.4648	0.2990	0.4164	0.4500	0.4657	0.4392	0.4078	0.4533	0.5955	0.3509
2002	0.4483	0.2987	0.4191	0.4566	0.4700	0.4343	0.4074	0.4376	0.6140	0.3541
2003	0.4359	0.2988	0.4219	0.4628	0.4664	0.4295	0.4058	0.4242	0.6325	0.3587
2004	0.4611	0.2979	0.4246	0.4435	0.4640	0.4388	0.3996	0.4149	0.6510	0.3629
2005	0.4863	0.2978	0.4275	0.4761	0.4618	0.4487	0.3926	0.4065	0.6696	0.3671
2006	0.5117	0.3053	0.4338	0.4823	0.4586	0.4585	0.3935	0.3973	0.6563	0.3713
2007	0.5373	0.3134	0.4403	0.4892	0.4558	0.4682	0.3955	0.3893	0.6428	0.3756
2008	0.5607	0.3201	0.4478	0.4972	0.4655	0.4778	0.3974	0.3801	0.6301	0.3830
2009	0.5691	0.3272	0.4537	0.5035	0.4717	0.4875	0.3994	0.3713	0.6355	0.3888
2010	0.5355	0.3344	0.4205	0.4710	0.4390	0.4432	0.4014	0.3624	0.6016	0.3556

Table 6: Theil indices for 10 selected countries, 1997 - 2010

	Central Africa Rep	Ethiopia	Ghana	Kenya	Mozambique	Nigeria	Senegal	Sierra Leone	South Africa	Tanzania
1997	0.5057	0.2616	0.2792	0.3409	0.4173	0.4160	0.3248	0.4671	0.6103	0.2058
1998	0.4704	0.2167	0.2831	0.3541	0.4321	0.4017	0.3245	0.4284	0.6117	0.2040
1999	0.4366	0.1757	0.2892	0.3680	0.4466	0.3875	0.3262	0.4177	0.6134	0.2084
2000	0.4041	0.1764	0.2961	0.3825	0.4594	0.3734	0.3004	0.3936	0.6151	0.2073
2001	0.3746	0.1775	0.3091	0.3944	0.4732	0.3595	0.2979	0.3681	0.6748	0.2163
2002	0.3443	0.1778	0.3153	0.4186	0.4873	0.3457	0.3279	0.3415	0.7387	0.2201
2003	0.3394	0.1745	0.3218	0.4320	0.4820	0.3336	0.9823	0.3228	0.8058	0.2293
2004	0.4047	0.1689	0.3284	0.4183	0.4761	0.3529	0.8218	0.3038	0.8770	0.2366
2005	0.4753	0.1688	0.3362	0.4934	0.4717	0.3758	0.2929	0.2971	0.9476	0.2441
2006	0.5531	0.1863	0.3493	0.4780	0.4456	0.3982	0.2782	0.2786	0.8943	0.2518
2007	0.6390	0.1960	0.3638	0.4980	0.4391	0.4205	0.2800	0.2764	0.8375	0.2597
2008	0.6978	0.1953	0.3811	0.5220	0.4792	0.4430	0.2823	0.2630	0.7880	0.2747
2009	0.7822	0.2019	0.3948	0.5409	0.4974	0.4652	0.2848	0.2512	0.8041	0.2864
2010	0.6846	0.2095	0.3302	0.4613	0.4179	0.3704	0.2876	0.2396	0.7044	0.2300

Table 7: Poverty Measures - Head count ratios (10 selected countries, 1997-2010)

	Central Africa Rep	Ethiopia	Ghana	Kenya	Mozambique	Nigeria	Senegal	Sierra Leone	South Africa	Tanzania
1997	0.6624	0.7008	0.1657	0.1408	0.7894	0.9573	0.0958	0.3784	0.0324	0.5977
1998	0.6317	0.7610	0.1810	0.1531	0.7801	0.9608	0.0908	0.4462	0.0385	0.5526
1999	0.6469	0.7758	0.1005	0.1778	0.7671	0.9697	0.0917	0.5594	0.0438	0.5468
2000	0.6287	0.8489	0.1749	0.2322	0.7996	0.9427	0.1204	0.5010	0.0477	0.5621
2001	0.6076	0.8506	0.2396	0.2550	0.8290	0.7628	0.1231	0.4426	0.0499	0.5700
2002	0.6116	0.8635	0.1885	0.2824	0.7420	0.7139	0.1359	0.3783	0.0540	0.5463
2003	0.6361	0.9041	0.1644	0.3064	0.7318	0.5146	0.1364	0.4635	0.0574	0.5826
2004	0.6238	0.9096	0.1332	0.2952	0.7045	0.4079	0.1482	0.4929	0.0567	0.5846
2005	0.6412	0.8231	0.1279	0.3587	0.6580	0.2583	0.1603	0.5358	0.0566	0.5453
2006	0.6526	0.7436	0.1433	0.3285	0.6296	0.4072	0.1528	0.5317	0.0385	0.5423
2007	0.6584	0.6538	0.1380	0.2991	0.5942	0.2117	0.1400	0.4784	0.0284	0.5441
2008	0.6477	0.5705	0.1170	0.3482	0.5386	0.3746	0.1560	0.4328	0.0242	0.5178
2009	0.6755	0.4282	0.1241	0.3123	0.5299	0.2720	0.1270	0.3872	0.0244	0.4988
2010	0.6528	0.3573	0.0722	0.2585	0.5185	0.2550	0.1322	0.3596	0.0080	0.4274

Table 8: Poverty Measures - FGT (2) - (10 selected countries, 1997-2010)

	Central Africa Rep	Ethiopia	Ghana	Kenya	Mozambique	Nigeria	Senegal	Sierra Leone	South Africa	Tanzania
1997	0.2315	0.1210	0.0188	0.0086	0.2410	0.5465	0.0071	0.0632	0.0023	0.1037
1998	0.2012	0.1402	0.0218	0.0111	0.2294	0.5549	0.0067	0.0926	0.0029	0.0920
1999	0.2032	0.1389	0.0103	0.0157	0.2178	0.5888	0.0069	0.1489	0.0036	0.0899
2000	0.1841	0.1850	0.0224	0.0260	0.2452	0.4817	0.0085	0.1059	0.0042	0.0954
2001	0.1652	0.1853	0.0351	0.0321	0.2749	0.2409	0.0081	0.0745	0.0044	0.0986
2002	0.1612	0.1953	0.0261	0.0399	0.1972	0.2091	0.0119	0.0542	0.0048	0.0922
2003	0.1676	0.2388	0.0226	0.0474	0.1942	0.1157	0.0160	0.0740	0.0052	0.1046
2004	0.1648	0.2414	0.0180	0.0485	0.1800	0.0807	0.0195	0.0797	0.0050	0.1061
2005	0.1795	0.1614	0.0178	0.0637	0.1579	0.0423	0.0192	0.0913	0.0049	0.0940
2006	0.1923	0.1245	0.0205	0.0558	0.1478	0.0814	0.0190	0.0865	0.0033	0.0939
2007	0.2030	0.0961	0.0197	0.0495	0.1345	0.0325	0.0177	0.0673	0.0023	0.0954
2008	0.2029	0.0767	0.0162	0.0607	0.1140	0.0726	0.0201	0.0548	0.0019	0.0873
2009	0.2225	0.0498	0.0173	0.0522	0.1108	0.0459	0.0170	0.0443	0.0020	0.0816
2010	0.1905	0.0412	0.0096	0.0382	0.1008	0.0395	0.0180	0.0384	0.0004	0.0603

Table 9: Empirical mean income in constant 2005 prices

	Central Africa Rep	Ethiopia	Ghana	Kenya	Mozambique	Nigeria	Senegal	Sierra Leone	South Africa	Tanzania
1997	517.70	448.32	1248.23	1352.14	369.10	153.57	1380.93	1153.20	4060.23	497.03
1998	552.51	400.33	1222.72	1330.91	378.35	147.91	1401.84	888.80	4004.71	526.92
1999	518.97	385.22	1604.95	1267.01	388.93	130.83	1387.23	628.17	3996.63	533.51
2000	532.12	334.83	1254.42	1127.69	371.67	182.25	1286.84	716.84	4042.25	520.86
2001	547.17	334.31	1060.14	1085.26	358.47	377.31	1273.35	794.05	4144.34	516.84
2002	529.91	324.93	1213.80	1034.44	454.83	418.17	1225.77	849.77	4204.66	537.83
2003	493.66	289.36	1307.96	996.45	458.22	617.24	1225.55	707.21	4300.60	513.31
2004	528.94	287.18	1460.80	925.69	481.24	775.38	1189.60	664.10	4534.81	514.51
2005	530.42	357.54	1498.53	924.91	518.88	1097.15	1165.65	608.30	4771.97	550.12
2006	538.77	407.70	1436.33	1001.72	530.10	811.96	1195.59	606.12	5208.07	555.82
2007	554.49	461.89	1487.89	1081.16	549.85	1302.87	1243.52	652.01	5512.28	557.50
2008	596.16	513.96	1644.19	998.46	603.76	910.59	1192.09	685.46	5570.20	588.86
2009	563.32	615.10	1618.33	1090.18	620.15	1176.93	1299.65	718.41	5654.02	613.53
2010	568.02	679.40	1829.84	1109.40	643.34	1073.12	1282.47	732.54	6067.00	643.38

Source: Penn World Table 8.0